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ESSAIS SUR LA MODELISATION DE LA DYNAMIQUE DU TAUX DE CHANGE
A TRAVERS LES ENSEIGNEMENTS DE LA FINANCE COMPORTEMENTALE

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ESSAYS IN EXCHANGE RATE DYNAMICS MODELLING
THROUGH LESSONS FROM BEHAVIOURAL FINANCE

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General Introduction:
Challenging the Difficulty of Modelling Exchange Rate Dynamics

1. The starting point: the failure of traditional exchange rate models

Paul A. Samuelson was one of the first economists to generalize and apply mathematical methods for the study of physics and biology to economics. In his book, *Foundations of Economic Analysis* (1947) - derived from his doctoral dissertation at Harvard University - Samuelson applies mathematical tools from the classical thermodynamics methods exposed by Gibbs (1846) to economics. Samuelson (1947) sows the seeds of agents’ maximising behaviours and proposes the stability of equilibrium as the main source of operationally meaningful theorems for economic systems.

Later, Muth (1961) and then Lucas (1972) refine the concepts put forward by Samuelson and come up with the rational expectations hypothesis (REH).

The REH states that based on all available information \( I_t \), the forecast of the price of an asset by an agent at time \( t \) for \( t+1 \) \((s^a_{t+1}/I_t)\) is on average equal to its actual value in \( t+1 \) plus an error term \( \varepsilon_t \):

\[
s^a_{t+1}/I_t = E(s_{t+1}/I_t) + \varepsilon_t \quad \text{with} \quad E(\varepsilon_t/I_t) = 0
\]

Thus, REH claims that agents do not make systematic errors when they forecast the future value of an asset \( E(\varepsilon_t/I_t)=0 \). Eventual forecasting errors made by agents are related to random unexpected information shocks \( \varepsilon_t \) not taken into account in the stock of information held by agents at time \( t \).

The REH rests on several assumptions. First, REH assumes the existence of a unique representative agent in the market. In other words, agents have homogeneous expectations. Secondly, agents are supposed to know the true and unique model of asset price determination and are able to compute the fundamental value of the price of the asset. Thirdly, agents understand the full complexity of the world and can process all the information coming to the market.

Rational expectations theory is the basis of the efficient market hypothesis (EMH). According to Fama (1965), a market is informationally efficient if the price of an asset reflects all the relevant information. In other words, the market is informationally efficient if
the price of the asset \( s_t \) is always equal to its fundamental value \( f_t \), given all the available information:

\[
s_t = E(f_t/I_t) = E_t(f_t)
\]

The REH-EMH paradigm has been abundantly used in economics by Neo-classicals (Lucas, Prescott, Barro, etc.), Monetarists (Friedman, etc.) and Keynesians (Mankiw, Romer, Akerloff, etc.). The predominance of the REH in economics is explained by several reasons. First of all, the REH appeared as the first hypothesis able to counter the limits of previous hypotheses on agents’ expectations such as static expectations or adaptive expectations. Secondly, REH is seen as an analytical condition or a technical mean that allows coordinating individual agents’ decisions and helps resolving general equilibrium models. Thirdly, models based on the REH have provided explanations of major phenomena in the field of economics and finance. As a result, many economists stick to the REH-EMH hypotheses for lack of a better alternative and because assuming economic agents are rational is convenient from a modelling point of view. The dominance of the REH-EMH paradigm has been such that it has concealed other alternative theories that counter the REH (such as the theory of bounded rationality put forward by Simon (1955)).

The REH-EMH paradigm is the basis of traditional models of exchange rate determination such as portfolio balance models (Dornbush and Fischer (1980)) and monetary models (Dornbush (1976), Frenkel (1976), Mussa (1976)).

Despite the attractiveness of the REH-EMH paradigm, empirical works by Meese and Rogoff (1983) and later Cheung, Chinn and Garcia Pascual (2005) put several doubts on exchange rate models based on the REH-EMH theory; even if some researchers (perhaps nostalgic ones) still try to save such models (Engle, Mark and West (2007)). These doubts are justified by the poor results offered by traditional models to explain and forecast exchange rate dynamics. Such models led also to unresolved puzzles associated to exchange rate dynamics such as the disconnection puzzle (why are exchange rates often disconnected from their fundamentals?); the excess volatility puzzle (why are exchange rates more volatile than their fundamentals?); the forward bias (why are forward exchange rates poor predictors of future exchange rates?).

We claim that the REH-EMH theory should not be judged by its elegance but by its capacity to withstand empirical testing. A majority of researchers now agree that the main
empirical predictions of REH-EMH models have not been borne out by the facts. The failure of traditional exchange rate models based on the REH-EMH paradigm led many researchers to ask about the relevance of the REH-EMH hypotheses and to reconsider such hypotheses.

2. Reconsidering the theoretical hypotheses of traditional models

2.1 From the reconsideration of the REH-EMH paradigm…

The reaction to the empirical failure of REH-EMH models has been to look for alternative modelling approaches. This reaction has been stimulated by the emergence of a new branch of economic thinking first introduced by Simon (1955) and later by Kahneman, Tversky, Thaler, Shleifer and others. We examine the main ideas behind this school of thought that is sometimes called behavioural economics or behavioural finance when applied to financial markets. The starting point of behavioural finance is the large body of evidence that has accumulated over time indicating that individuals do not behave in accordance with the REH-EMH paradigm.

We mention here a few anomalies relative to the REH and how those anomalies help understanding exchange rate dynamics empirically.

The representative bias was highlighted by Kahneman and Tversky (1974). They show that individuals tend to set up general rules from specific observations. From a temporal perspective, the representative bias is translated into a momentum bias. The momentum bias means that agents tend to overweight the past recent information in their decisions.

The abundant use of chartist rules in the foreign exchange market (Allen and Taylor (1992), Menkhoff and Taylor (2007)) justifies this bias among market agents empirically. Indeed, chartist rules such as momentum rules forecast future exchange rate dynamics by interpolating past movements of exchange rates. The momentum bias has become a stylised fact since surveys among foreign market practitioners confirm the abundant use of momentum rules in every foreign exchange places around the world: Hong-Kong, Singapore and Tokyo (Lui and Mole (1998), Cheung and Wong (2000)); London (Allen and Taylor (1992), Cheung, Chinn and Marsh (2004)) and the United States (Cheung and Chinn (2001)).
The anchoring bias was discovered by Kahneman and Tversky (1974). They show that in situations of uncertainty, individuals tend to proceed to a numerical evaluation by relying on an external number whether relevant or not.

The anchoring bias is illustrated into the foreign exchange market by the existence of psychological barriers in exchange rate dynamics. Psychological barriers are observed when market agents attach importance to a given threshold value for the price of a currency. The exchange rate fluctuates close to the threshold value and does not go beyond this threshold: the exchange rate volatility is low. Once the exchange rate overtakes the threshold, it wanders away from it and reaches another threshold. Exchange rate volatility becomes higher during this movement. De Grauwe and Decupere (1992) provide empirical evidence on the existence of psychological barriers in the foreign exchange market. Westerhoff (2003) theorises this stylised fact to explain volatility clustering effects in exchange rate dynamics (i.e. the fact that exchange rates alternate between periods of high volatility and periods of low volatility).

The confirmation bias was highlighted by Wason (1960). Wason shows that individuals tend to favour information that confirms their hypotheses or the output of their models regardless of whether this information is true. The confirmation bias is part of the cognitive dissonance (Festinger (1957)). Festinger shows that agents tend to overweight the information that confirms their decisions and underweight or even ignore the information that goes against their opinion.

From an empirical perspective, De Grauwe (2000) shows that because it is difficult to predict exchange rate dynamics, agents tend to rely on fundamentals that confirm the recent past exchange rate dynamics and ignore other fundamentals. For example, market agents justify the depreciation of the euro against the dollar between January 1999 and December 2002 by higher growth prospects in the United States than in Europe. Also, market agents blamed the huge external deficits of the United States relative to the euro zone to justify the depreciation of the dollar vis-à-vis the euro between January 2003 and December 2004. Further, Cheung and Chinn (2001) show that fundamentals considered by market agents in the determination of exchange rates vary across time periods. For example, market agents gave higher weights to money supply and trade deficits between 1990 and 1995 contrary to inflation, interest rates and unemployment. Conversely, between 1995 and 2000, market agents gave more importance to inflation, interest rates and unemployment and less to money supply and trade deficits. Bachetta and van Wincoop (2005) theorise this stylised fact in their
scapegoat model. A fundamental variable is taken as a scapegoat to explain exchange rate movements in a given period of time.

Overconfidence shows that individuals’ subjective confidence in their judgments is reliably greater than their objective accuracy.

The survey by Oberleshner and Osler (2004) justifies overconfidence among foreign exchange market practitioners. Odean (1999) uses overconfidence to justify the hot potato effect in the foreign exchange market. Overconfidence leads dealers to increase their belief on their ability to find better investment opportunities. They thus increase their portfolio turnover. This increased turnover hence explains the large amount of positions passed among dealers. Other studies like Daniel, Hirschleifer and Subramanyam (1998) or Barberis and Thaler (2002) use overconfidence to justify respectively the disconnection of exchange rates from fundamentals and excess volatility in currency prices.

Regarding the EMH, behavioural finance has also highlighted phenomena in financial markets that disconnect the price of the currency from its fundamental value. Hence, currency prices are not always equal to their fundamental value.

One of the most popular phenomena is herding behaviour or mimetism (Keynes (1936)). Financial markets are for individuals a complex and uncertain environment. To survive in such an environment, agents tend to reproduce other agents’ behaviours. Herding behaviours trigger information cascades (Bikhchandani, Hirschleifer and Welch (1992)). Information cascades occur when agents follow the actions of other agents independently of their own private information. Osler (2002) shows evidence that specific rules (such as stop-loss orders) used by foreign exchange market practitioners are based on other agents’ behaviours, and are likely to trigger information cascades. Although rational at individual levels, mimetism leads to irrational phenomena at global levels such as bubbles \( i.e. \) disconnections of asset prices from their fundamental value.

The EMH assumes also that arbitrageurs erase eventual discrepancies between asset prices and their fundamental value. Researchers have highlighted several limits to arbitrage in financial markets.

DeLong, Shleifer, Summers and Waldmann (1990) show that the noise brought by irrational agents (noise traders) increases the risk of holding the risky asset. This increased
risk in turn limits the intervention of rational agents (arbitrageurs) in the market. Besides, DeLong et al. (1990) show that the increased risk generated by irrational agents to hold the risky asset induces higher returns for noise traders than for arbitrageurs. As irrational agents earn higher returns than rational agents, noise traders survive in the market in the long run. As a result, disconnections of the price of the asset from its fundamental value do not disappear even in the long run. Empirically, the effect of noise traders in the foreign exchange market can be observed through price manipulations by large players (Rankin (1999), Corsetti, Pesenti and Roubini (2001)), the effects of rumours (Oberlechner and Hocking (2004)), etc.

Thus, a large body of evidence in financial markets counters the fact that agents behave in accordance with the REH-EMH paradigm. Our research path departs from the REH-EMH hypotheses. Rather, we assume agents are bounded rational. Bounded rationality is a concept put forward by Simon (1955). Simon argues that in decision making, individuals’ rationality is limited by the information they have, the cognitive limitations of their minds, and the finite amount of time they have to make decisions. This assumption does not mean that agents are irrational or stupid. The paradigm of bounded rationality is just more reasonable than the REH-EMH.

Indeed, the world is too complex for human beings to know the fundamental model of exchange rates and to be able to process all the available information concerning an asset. Instead, human beings draw simple rules - heuristics - from this complexity to compute the price of an asset (anchoring bias). Also, human beings cannot process all the information that comes to them. They will select some information and ignore other (representative bias, confirmation bias). Besides, agents are not bereft of any psychological dimension as stated by the REH-EMH. Damasio (2003) emphasises the importance of the emotional process in agents’ decisions and shows that psychological factors (e.g. overconfidence) do affect market agents’ decisions.

2.2 … To the birth of new theories of exchange rate determination

The willingness to depart from the REH-EMH paradigm has given birth to several promising theories in exchange rate determination. First, researchers have relinquished the concept of homogeneous expectations for the one of heterogeneous expectations. This turn has led researchers to set two theories: order flows models of exchange rate and behavioural
(heterogeneous agents) models of exchange rate. Secondly, the fact that agents are bounded rational and that they face a complex world led researchers to set the theory of imperfect knowledge economics.

Order flows models of exchange rate were pioneered by the work of Evans and Lyons (2002). These models belong to the broader field of microstructure theory. Order flows are defined as the net of buyer- and seller-initiated currency transactions. Order flows may be thought of as a measure of net buying pressure. Order flows theorists emphasise the importance of private information in the determination of asset prices relative to public information. Private information regroups the heterogeneous beliefs of market agents. Thus order flows can be seen as a proxy for agents’ heterogeneous expectations.

From an empirical perspective, order flows models of exchange rate provide better explanatory power of exchange rate dynamics relative to traditional models of exchange rate. This result holds in the short run as well as in the long run (Evans and Lyons (2002, 2006, 2008), Berger et al. (2008)). Order flows models also provide better forecasts than traditional models since they beat the random walk in the short run (Lindahl and Rime (2006), Rime et al. (2010)). Besides, models based on order flows also offer solutions to the exchange rate disconnection puzzle (Bachetta and van Wincoop (2006), Evans (2010)).

Behavioural (heterogeneous agents) models of exchange rate were set by the pioneered work of Frankel and Froot (1986) and later revisited by De Grauwe and Grimaldi (2007). Behavioural models of exchange rate are based on the stylised fact that two major agents interact in the foreign exchange market: chartists and fundamentalists. Chartists interpolate past trends of exchange rates to forecast future exchange rate dynamics. Fundamentalists forecast future exchange rates based on the spread between the observed exchange rate and its fundamental value.

A large credit has been attributed to this theory since the interaction between chartists and fundamentalists allows explaining exchange rate dynamics and especially the disconnection of exchange rates from their fundamental value. The works by Vigfusson (1997) and later Chan et al. (2000) validate empirically the theoretical models of Frankel and Froot (1986). Behavioural exchange rate models explain also other puzzles undermining exchange rate dynamics such as the excess volatility puzzle or volatility clustering effects (De Grauwe and Grimaldi (2007)).
The approach of Imperfect Knowledge Economics (IKE) was set by the pioneered work of Frydman and Goldberg (2007). Their approach follows neither REH-EMH models, nor behavioural finance models. In line with the Lucas’ (1976) critique, Frydman and Goldberg (2007) recognise that models that predetermine agents’ behaviours (such as REH-EMH models and behavioural finance models) are inadequate. Indeed, such models assume that agents act as robots i.e. in accordance with the exogenous rules specified by the modeller. Such models do not allow for endogenous evolutions in agents’ behaviours and unpredictable changes in the environment faced by agents. Instead, Frydman and Goldberg propose to partially predetermine the behaviour of agents by imposing qualitative restrictions in their models instead of quantitative ones.

IKE provides a new solution to the exchange rate disconnection puzzle. IKE shows that with incomplete knowledge, disconnections of exchange rates from fundamentals do not depend on whether prices are sticky or flexible as argued by past REH-EMH models. Rather, disconnections arise from the fact that market agents have to cope with an imperfect knowledge of the structure of the economy.

Thus theories that depart from the concept of REH-EMH offer a better understanding of exchange rate dynamics. Hence in our quest to build a robust model of exchange rate determination, we will take account of the lessons from the behavioural finance literature. Having clarified which theoretical path we follow, we indicate in the next section the structures of the models that are likely to offer the best fit for our modelling approach.

3. Improving the empirical structure of traditional models of exchange rate

The empirical failure of traditional models of exchange rate leads us to reconsider the econometric structure used in these models. Traditional models assume the existence of a symmetric world and a linear structure between the exchange rate and its fundamentals. The existence of a symmetric world implies that a shock on a given fundamental whether in the domestic or in the foreign economies will have the same effect on the exchange rate. A linear structure means that there is a stable relationship between the exchange rate and a given stock of fundamentals through time. Both hypotheses are not verified empirically.

1 The ideas from Frydman and Goldberg (2007) are also shared by practitioners who have a close experience with financial markets, notably Soros (1987).
First, a lot of studies provide evidence that investors react asymmetrically to news on a given fundamental between two economies (Prast and De Vor (2000), Galati and Ho (2001) and Andersen et al. (2003)). As a matter of facts, empirical results for the euro/dollar exchange rate suggest that market agents overweight news coming from the United States relative to news coming from the euro area. This fact gives more credit to the assumption of an asymmetric world. An asymmetric structure means that agents do not react the same way to the same shock in the domestic and in the foreign economies.

Secondly, a large body of literature (De Grauwe (2000), Cheung and Chinn (2001)) shows that some fundamentals may be important in the determination of exchange rates at some periods while not at others. De Grauwe and Vansteenkiste (2002) show that the dynamics of exchange rates and their fundamentals are characterised by structural breaks. Cheung, Chinn and Garcia Pascual (2005) showed that linear models with particular macroeconomic variables perform well in some periods but not in others. Also, models that take account of non-linear structures in the modelling of exchange rates based on fundamentals (Gandolfo, Padoan and Paladino (1990), Kilian and Taylor (2003), Cheung and Erlandsson (2005)) provide better explanatory and predictive results than traditional models. These facts give more credit to non-linear models. Non-linearities mean that exchange rates are not explained by the same set of fundamentals through time or equivalently that the relationship between exchange rates and a given stock of fundamentals is not stable through time.

Until now, econometrics offer two types of tools to model exchange rate dynamics based on non-linear structures. On the one hand, one can use non-linear models where regime switches depend on observable variables (threshold models and time-varying transition probabilities (TVTP) Markov switching models); and on the other hand, one can rely on non-linear models where regime switches are driven by unobservable variables (hidden or fixed transition probabilities (FTP) Markov switching models).

Threshold models imply that the parameters of the state equations vary according to the position of an observable variable relative to a threshold value. Threshold models are split in two categories. TAR models (Threshold AutoRegressive) - pioneered by Tong (1978) and Tong and Lim (1980) - imply that the transition between the state equations is sudden and depends on an indicative function that takes the values 0 or 1. Later Luukkonen, Saikkonen and Teräsvirta (1988), Luukkonen and Teräsvirta (1991) and Teräsvirta and Anderson (1992) propose an extension of TAR models into STAR models (Smooth Transition Autoregressive). In STAR models, state transitions are progressive and are modelled with a continuous
function bordered between 0 and 1. Generally, such models consider either a logistic function (LSTAR) or an exponential function (ESTAR).

TVTP Markov switching models were pioneered by the work of Diebold et al. (1994), Engel and Hakkio (1994) and Filardo (1994). In these models, the transitions between state equations depend on an observable state variable. The transition probabilities are allowed to vary over time depending on the value of the observable variable.

Hidden or FTP Markov switching models were pioneered by Goldfeld and Quandt (1973) and applied to time series by Hamilton (1989). Such models differ from threshold models and also from TVTP Markov switching models in that the transition between the state equations depends on an unobservable state variable that usually follows a Markov chain of order one. The transition probabilities are here constant through time and do not depend on any observable state variable.

Although undermined by a difficult implementation relative to linear models, nonlinear models - both threshold models and Markov switching models - provide a more suitable framework for the modelling of exchange rate dynamics. As a result, our research procedure will make use of these tools to model exchange rate dynamics.

4. Problematic and major challenges of the thesis

The objective of the thesis is to find a robust model that determines the dynamics of exchange rates at short, medium and long run horizons. The imposed challenge is that this model has to provide better explanatory and predictive powers of exchange rate dynamics than traditional models of exchange rate.

Given the above arguments, the hypotheses of a robust model of exchange rate determination have to depart from the REH-EMH paradigm. Our modelling approach draw lessons from behavioural finance. Our model takes account not only of macroeconomic fundamentals but also of behavioural and psychological components of market agents. This chosen path of research is justified by the importance of agents’ behaviours to understand exchange rate dynamics especially at short horizons. Such arguments have been emphasised by surveys of market practitioners (Cheung and Wong (2000), Cheung and Chinn (2001), Cheung, Chinn and Marsh (2004)). These surveys show that market psychology plays a major role in the determination of exchange rates in the short run (i.e. for horizons shorter than 6 months).
To build a robust exchange rate model, our modelling approach draws also lessons from non-linear econometrics. We rely on threshold models and Markov switching models. The difficulty of this challenge lies in the fact that we have to avoid falling in what Frisch (1970) - the founder of the Econometric Society - called playometrics\(^2\). The argument of Frisch means that a pure econometric model not based on any relevant theoretical concepts is simply not receivable. To counter this argument and to justify our econometric approach with regards to dubitative researchers about the use of econometrics (see also Hendry (1980)), we refine our research procedure. We compel to build a parsimonious and robust exchange rate model based on a relevant economic theory.

The question that one may raise is whether lessons from behavioural finance and non-linear econometrics are sufficient enough to build a robust model of exchange rate determination? This thesis puts forward some answers... but in all its modesty, this thesis provides only part of the answers.

5. Main results highlighted by the thesis

The first article analyses the environment of research that is, the foreign exchange market. The second article provides elements to understand the success of order flows models in exchange rate determination. The third article looks for the determinants of heterogeneous behaviours in the foreign exchange market. The fourth article proposes an unorthodox model of exchange rate determination based on conventions that prevail among market agents in the foreign exchange market.

5.1 Through the looking-glass: reconsidering efficiency in the foreign exchange market

This paper argues that market efficiency can be split into multiple and independent forms. We provide three definitions of market efficiency: fundamental efficiency, speculative efficiency and macroeconomic efficiency.

\(^2\) "Observations get a meaning only if they are interpreted by an underlying theory. Therefore, theory, and sometimes very abstract theory, there must be. And no kind of mathematical analysis in economics should be rejected just because it might be difficult and refined mathematics. But at the same time I have insisted that econometrics must have relevance for concrete realities - otherwise it degenerates into something which is not worthy of the name econometrics, but ought rather to be called playometrics"," dixit Frisch (1970)."
Fundamental efficiency (or Fama’s efficiency) holds in the market if, on the one hand, exchange rate dynamics reflect the evolution of fundamentals as stated by uncovered interest rate parity (UIP) and on the other hand, if speculation is not profitable in the market; i.e. if the return/risk ratio associated to a speculative strategy is not higher than the one associated to another investment strategy for a given amount of risk. Speculative efficiency prevails in the market if speculation is not profitable; that is if the return/risk ratio associated to a speculative strategy is not higher than the one associated to another investment strategy for a given amount of risk; and if the exchange rate is disconnected from its fundamental value.

Macroeconomic efficiency describes the ability of exchange rates to evolve according to their fundamentals. It implies not only the existence of a long run relationship between the exchange rate and its fundamentals; but also the existence of correction forces that reduce macroeconomic disequilibria related to exchange rate movements - such as current account deficits. A corollary of the first and second conditions is the possibility to forecast future exchange rate dynamics by using macroeconomic fundamentals.

For each form of efficiency, we define a set of empirical tests. Fundamental efficiency holds if UIP and the REH hold in the market. To assess speculative efficiency, we analyse the profitability of two speculative strategies commonly used among foreign exchange market practitioners: a momentum strategy and a carry trade strategy. To test macroeconomic efficiency we analyse the predictive performances of a fundamental model of exchange rate. Empirical tests are based on the euro/dollar, the pound/dollar and the yen/dollar exchange rates.

Results show that in the short run (between 1 month and 1 year) pure inefficiency prevails in the foreign exchange market. This result is justified by the failure of UIP, the possibility to make profits from momentum and carry trade strategies and the existence of long-lasting misalignments between the exchange rate and its fundamentals at short horizons. In the medium term (between 1 year and 2 years), speculative efficiency characterises foreign exchange market efficiency. Indeed, UIP holds thus limiting profits from carry trades; forecasts based on momentum rules worsen thus limiting the profitability of momentum rules.

In the long run (from 5 years on), macroeconomic efficiency holds in the foreign exchange market. Indeed, fundamental models provide significant explanatory and predictive powers for exchange rate dynamics. Fundamental efficiency - Fama’s efficiency - is rejected in the foreign exchange market whatever horizon considered. This result is justified by the failure of UIP in the short run (between 3 months and 1 year), the poor performances of fundamental
models in the short/medium term (from 1 month to 2 years) and the rejection of REH (at all horizons).

The main point of this article is that traditional models of exchange rate perform well in the long run (from 5 years on) but not in the short/medium run. Therefore, at short/medium run horizons, there must be other forces than macroeconomic fundamentals that explain exchange rate dynamics. This article argues that market psychology (overreaction, bandwagon effects, rumours, etc.) can play the role of such forces. As a result, we claim that a robust model of exchange rate should include not solely macroeconomic fundamentals but also behavioural or psychological agents’ components to provide a relevant explanation of exchange rate dynamics. One may wonder whether a model of this kind already exists.

5.2 Inside the black box: why are order flows models of exchange rate more competitive than traditional models of exchange rate?

This article investigates the outstanding success of order flows models of exchange rate (Lyons (2001), Evans and Lyons (2002)). As a matter of facts, order flows models provide better explanatory and predictive powers in forecasting exchange rate dynamics than traditional models not solely in the long run, but also in the short run (Berger et al. (2008)).

Our intuition is that the difference of performances between traditional models of exchange rate and order flows models is due to the fact that these models may not consider the same stock of information. We therefore look inside the black box of order flows models to unveil the information contained in order flows.

We set a theoretical model that embeds all the information available in the foreign exchange market that is likely to affect exchange rate determination. The model aims at observing how the initial information is included into the final price of the currency. The model relies on a behavioural exchange rate model and a microstructure model.

The article puts forward three results. First, model simulations replicate important stylised facts observed in the foreign exchange market. In the short run, the exchange rate is disconnected from its fundamental value but not from order flows. In the long run, the exchange rate returns towards its fundamental value and remains still close to order flows. Customer and interdealer order flows are highly correlated with exchange rate dynamics at all horizons. Besides the hot potato effect magnifies the amount of interdealer order flows relative to the amount of customer order flows. Secondly, the article argues that the foreign
exchange market is intrinsically inefficient. Information is distorted in the final price by agents’ behaviours (behavioural noise) and by the trading mechanism peculiar to the foreign exchange market (microstructure noise). Thirdly, the article explains why order flows provide an answer to the exchange rate disconnection puzzle. Order flows contain information processed by agents while traditional models only consider raw information. Processed information in order flows includes a time-varying weight of fundamental information (both public and private), behavioural agents’ information (both public and private) and microstructure information. Conversely, information considered in traditional models only includes public fundamental information. The difference in the types of information considered by order flows models and traditional models explain why order flows models provide higher explanatory and predictive powers of exchange rate dynamics relative to traditional models.

This article claims that traditional models will never do better than order flows models even if we take account of alternative specifications (e.g. non-linear) for traditional models. The advantage of order flows models is to take account of the behavioural dimension of agents. Indeed, order flows include information that has been processed by agents (fundamental information plus behavioural noise plus microstructure noise) while traditional models of exchange rate only consider raw or unprocessed information (i.e. fundamental information). This article thus confirms the point underlined in the first article: market agents’ psychology plays a significant role in the determination of exchange rates. Order flows theorists do not hide the behavioural dimension of order flows models. They state that order flow is a proxy for heterogeneous expectations of market agents. However, order flows are still a black box. This problem implies that order flows models do not resolve the puzzle of exchange rate determination since researchers do not know yet the determinants of order flows. One way to clarify the information contained in order flows would therefore be to model expectations’ heterogeneity contained in order flows. Heterogeneous agents models (Frankel and Froot (1986) and De Grauwe and Grimaldi (2007)) perform this task.
5.3 On the determinants of heterogeneous behaviours in financial markets: evidence from non-linear models

Following Frankel and Froot (1986) and De Grauwe and Grimaldi (2007), this article models the heterogeneity of agents’ behaviours by relying on two types of agents: chartists and fundamentalists.

The article shows that models based on heterogeneous agents significantly explain exchange rate dynamics. However, the related literature does not investigate the empirical determinants of heterogeneous behaviours. The paper first analyses the link between heterogeneous behaviours in the euro/dollar foreign exchange market and the European and US stock markets. Then, the paper analyses the empirical determinants of heterogeneous behaviours. The period of analysis spans January 1990 until December 2009.

First, results show that the homogeneity of heterogeneous behaviours across markets increases all over the period. For example, at the beginning of the period, shocks affecting only the foreign exchange market or only the stock market did not generate homogeneous behaviours on the three markets, contrary to shocks at the end of the period. This observation justifies the increasing financial integration between stock markets and the foreign exchange market. This increasing homogeneity in market behaviours increases in turn the instability of financial markets in periods of financial turmoil. Besides, the causality of behaviours is significant and strong within markets that trade the same asset (here between the European and US stock markets) but weaker or even not significant between two markets that trade different assets (here between either the European or the US stock markets, and the foreign exchange market).

Secondly, we find that risk aversion (approximated by implied volatility on option prices) is more likely to explain heterogeneous behaviours in financial markets than macroeconomic fundamentals. When risk aversion is high (low), fundamentalists (chartists) dominate the market. As a result, fundamentalists dominate in times of crisis (when risk aversion increases) while chartists dominate in times of booms (when risk aversion decreases). From a behavioural perspective, agents seem therefore more rational in times of crisis (since they rely more on fundamentals to forecast exchange rates) than in times of booms (where agents rely more on chartist analysis and ignore macroeconomic fundamentals).

Based on this stylised fact we build a behavioural forecasting rule. This rule provides better out-of-sample forecasts of future asset prices than the random walk. This observation stands in the long run as well as in the short run. This result proves that taking account of
stylised facts about agents’ behaviours is useful for explaining and forecasting asset price dynamics. This article thus confirms the underlying point of the thesis i.e. considering agents’ behaviours is important to build robust models of exchange rate determination.

Heterogeneous agents models present however two major drawbacks. First, these models have to specify an arbitrary value for the fundamental exchange rate for the specification of the fundamentalist rule. Specifying a unique fundamental exchange rate limits the objectivity of the heterogeneous agents’ approach because empirically multiple definitions of the fundamental exchange rate prevail in the market. The second drawback lies in the fact that heterogeneous agents models fully predetermine the behaviour of economic agents. Indeed, such models associate an exogenous rule to each agent. Agents therefore have to comply to a given rule. The problem is that empirically, agents tend to modify their models through time often by following trial-and-error strategies. One may wonder whether one can find a model that allows for this endogenous change in agents’ behaviours?

5.4 Conventions in the foreign exchange market: can they really explain exchange rate dynamics?

This paper provides an unorthodox way to model exchange rate dynamics based on conventions that prevail among market agents. The intuition behind the convention model is based on a stylised fact highlighted by De Grauwe (2000). De Grauwe argues that agents tend to look for fundamentals that confirm the observed movements in the exchange rate. For instance, the large depreciation of the euro relative to the dollar between January 1999 and December 2002 was attributed to the strong growth performance in the United States relative to the euro zone. On the contrary, the appreciation of the euro relative to the dollar between December 2002 and December 2004 was justified by large current account deficits in the United States compared to the euro zone. Bachetta and van Wincoop (2005) theorised this idea in the scapegoat model. A fundamental variable is taken as a scapegoat to explain exchange rate dynamics in a given period of time. Our approach differs strongly from Bachetta and van Wincoop (2005). Our convention model borrows more elements from the Imperfect Knowledge Economics (IKE) approach pioneered by Frydman and Goldberg (2007).

We first build a theoretical model to explain the mechanisms underlying the formation of market conventions. The simulated exchange rate from the theoretical convention model
replicates several stylised facts highlighted empirically in exchange rates dynamics. We then test this model empirically on the euro/dollar exchange rate. The period of analysis spans January 1995 to December 2008. We rely on two alternative methods. The first method is a macroeconomic analysis that aims at explaining the euro/dollar movements by relying on the consensus of economists. This method is based on the analysis of the fundamentals used by the economic and financial literature to justify the euro/dollar dynamics. The second method is based on an econometric approach. We estimate a time-varying parameters model and assess the predictive performances of the selected fundamental models to find the conventions that drive the euro/dollar dynamics.

Both methods show that market switches between fundamentals considered in a bull convention and in a bear convention explain the euro/dollar dynamics between January 1995 and December 2008. The analysis thus shows the existence of a non-linear relationship between fundamentals and the euro/dollar exchange rate. In other words, some fundamentals may be more important at some periods of time for the determination of exchange rate dynamics while other fundamentals are important at other periods of time.

Both methods identify three major conventions in the euro/dollar market. The first convention is the new economy convention that covered the period January 1995 - December 2000. Investors were relatively more optimistic in the growth prospects of the US economy than in European economies. The dollar experiences a strong appreciating trend in this period. Between January 2001 and June 2003, the market relies on a bear convention based on the huge external debt of the US economy. The dollar starts a strong depreciating trend in this period. Then, between July 2003 and December 2005, two competing conventions prevailed in the market. A bear convention that focused mainly on the large US current account deficits; and a bull convention that pointed to the spectacular recovery of the US economy from the internet bubble burst. During this period the dollar alternates between short-lasting appreciating and depreciating trends according to whether the bull convention dominates the bear one. After January 2006, fundamentals worsened in the US economy. The bear convention started to dominate the bull one. The spark of the subprime crisis in June 2007 definitely led to the domination of the bear convention in the market.

The article then tests the predictive power of the convention model with regards to alternative specifications. Results show that at horizons longer than 1 month, the convention model provides better out-of-sample forecasts than traditional exchange rate models and than the simple random walk. As a result, this article shows that convention theory appears as a promising way to explain and predict exchange rate dynamics.
References


Introduction Générale:

De la Difficulté de Modéliser la Dynamique des Taux de Change

1. Le point de départ: l’échec des modèles traditionnels de détermination des taux de change


Muth (1961) et Lucas (1972) reprennent et affinent la théorie développée par Samuelson en posant l’hypothèse d’anticipations rationnelles (HAR). L’HAR suppose que sur la base de toute l’information disponible $I_t$, la prévision du prix d’un actif en $t$ pour $t+1$ ($s_{t+1|t}$) est en moyenne égale à la valeur réalisée de cette variable en $t+1$, plus un terme d’erreur :

$$s_{t+1|t} = E(s_{t+1}/I_t) + \epsilon_t \quad \text{avec} \quad E(\epsilon_t/I_t) = 0$$

L’HAR suppose ainsi que les agents ne font pas d’erreurs systématiques dans la prévision de la valeur future du prix d’un actif ($E(\epsilon_t/I_t)=0$). Les éventuelles erreurs de prévisions faites par les agents sont justifiées par des chocs de nouvelles aléatoires non anticipés.


L’HAR constitue le fondement de l’hypothèse d’efficience informationnelle des marchés (HEM). Selon Fama (1965), un marché est informationnellement efficient si le prix
d’un actif $s_t$ reflète toujours la valeur fondamentale $f_t$ de l’actif compte tenu de toute l’information disponible :

$$s_t = E(f_t/I_t) = E_t(f_t)$$

Le paradigme de l’HAR-HEM a été abondamment utilisé en économie par les néoclassiques (Lucas, Prescott, Barro, etc.), les monétaristes (Friedman, etc.) et les keynésiens (Mankiw, Romer, Akerloff, etc.). Cette utilisation fréquente est justifiée par plusieurs raisons. Premièrement, l’HAR est la première hypothèse sur les anticipations des agents venant contrer les limites des précédentes hypothèses (les hypothèses d’anticipations statiques ou celles d’anticipations adaptatives). Deuxièmement, l’HAR apparaît comme une condition analytique nécessaire pour coordonner les décisions individuelles des agents et pour résoudre les modèles d’équilibre général. Troisièmement, les modèles économiques basés sur l’HAR ont permis d’apporter des explications à d’importants phénomènes dans le domaine de l’économie et de la finance. En conséquence, de nombreux chercheurs s’appuient sur le paradigme de l’HAR-HEM par manque de meilleure(s) hypothèse(s) alternative(s) mais également parce que l’HAR apparaît comme un outil satisfaisant en matière de modélisation économique. La prédominance de l’HAR-HEM a été telle que ce paradigme a occulté d’autres théories alternatives telles que la théorie de la rationalité limitée développée par Simon (1955).

L’HAR-HEM constitue la base des modèles traditionnels de détermination des taux de change tels que les modèles de portefeuille (Dornbush et Fischer (1980)) ou les modèles monétaires (Dornbush (1976), Frenkel (1976), Mussa (1976)). En dépit de l’attrait de l’HAR-HEM, les travaux empiriques entrepris par Meese et Rogoff (1983) puis par Cheung, Chinn et Garcia Pascual (2005) soulèvent des doutes sur la pertinence des modèles de change basés sur l’HAR-HEM. Ces doutes sont justifiés par le faible pouvoir explicatif et prédictif des modèles traditionnels de change. Ces modèles ont également conduit à des énigmes sur la dynamique des taux de change telles que l’énigme de la déconnexion des taux de change (pourquoi l’évolution des changes est-elle déconnectée de celles des fondamentaux ?) ; l’énigme de l’excès de volatilité du change (pourquoi les taux de change sont-ils plus volatils que leurs fondamentaux ?) ; l’énigme de la prime de terme (comment expliquer que les taux de change à terme sont de mauvais prédicteurs des taux de change futurs ?)

La théorie de l’HAR-HEM ne doit pas être jugée par son élégance théorique mais plutôt par sa capacité à expliquer les phénomènes observés empiriquement. Les chercheurs
reconnaissent que les modèles de change basés sur l’HAR-HEM offrent des performances empiriques non satisfaisantes. Ces faits ont conduit de nombreux chercheurs à s’interroger sur la pertinence de l’HAR-HEM et même à reconsidérer ce paradigme.

2. La reconsidération des hypothèses des modèles traditionnels de change

2.1 De la reconsidération du paradigme de l’HAR-HEM…

Face à l’échec empirique des modèles traditionnels de change basés sur l’HAR-HEM, les chercheurs se sont tournés vers des approches alternatives et notamment vers la finance comportementale. La finance comportementale a été développée par Simon (1955) puis par Kahneman, Tversky, Thaler et Shleifer. La finance comportementale s’appuie sur des faits empiriques (ou anomalies) qui vont à l’encontre du paradigme de l’HAR-HEM. Nous mentionnons ici quelques unes de ces anomalies. Nous explicitons également comment ces anomalies permettent de comprendre la dynamique des taux de change au niveau empirique.

Le biais de représentativité a été mis en évidence par Kahneman et Tversky (1974). Les deux auteurs montrent que les individus ont tendance à inférer des règles générales à partir de faits empiriques spécifiques. D’un point de vue temporel, le biais de représentativité se traduit par un biais momentum. Le biais momentum signifie que les agents ont tendance à surpondérer l’information du passé récent dans leurs décisions.


pour le prix de la devise. Le taux de change fluctue autour de cette valeur seuil et la dépasse rarement. Une fois la valeur seuil dépassée, le taux de change s’éloigne fortement de cette valeur et rejoint une autre valeur seuil. De Grauwe et Decupere (1992) fournissent des preuves empiriques sur l’existence de ces barrières psychologiques dans le marché des changes. Westerhoff (2003) théorise ce fait stylisé en expliquant les bouquets de volatilité observés dans la dynamique des taux de change (c’est-à-dire le fait que les taux de change alternent entre des périodes de forte volatilité et des périodes de faible volatilité).

Le biais de confirmation a été découvert par Wason (1960). Wason montre que les individus tiennent plus favorablement compte de l’information qui confirme leurs idées ou les résultats de leurs modèles. Le biais de confirmation fait partie des dissonances cognitives (Festinger (1957)). Festinger montre que les agents surpondèrent l’information qui confirme leurs décisions et sous-pondèrent voire ignorent l’information remettant en cause leurs décisions.


L’excès de confiance s’illustre lorsque la confiance que les agents attribuent à leur jugement est excessive. L’enquête d’Oberleshner et Osler (2004) auprès de praticiens du

Concernant l’HEM, la finance comportementale a également mis en évidence des phénomènes qui remettent en cause la condition de stricte égalité entre le prix d’une devise et la valeur fondamentale de cette devise. Les comportements mimétiques (Keynes (1936)) illustrent cet argument. Les marchés financiers constituent pour les individus un environnement complexe et incertain. Pour survivre dans un tel environnement, certains individus ont tendance à reproduire le comportement des autres individus. Ces comportements mimétiques déclenchent des cascades informationnelles (Bikhchandani, Hirschleifer et Welch (1992)). Lors de cascades informationnelles, les individus suivent le comportement des autres agents sans tenir compte de leur information privée personnelle. Osler (2002) montre que l’utilisation de règles d’investissement telles que les *stop-loss orders* de la part des agents sur le marché des changes est susceptible de déclencher des cascades informationnelles. Bien que rationnelles au niveau individuel, le mimétisme conduit à des phénomènes irrationnels au niveau du marché tels que des bulles c’est-à-dire des déconnexions des prix d’actifs de leur valeur fondamentale.

L’HEM suppose également que l’action des arbitragistes conduit à éliminer les éventuels écarts de valeur entre le prix d’un actif et sa valeur fondamentale. Les chercheurs ont mis en évidence plusieurs limites à l’arbitrage sur les marchés financiers. De Long, Shleifer, Summers et Waldmann (1990) montrent que le bruit généré par les agents irrationnels (*noise traders*) augmente d’une part le risque associé à la détention de l’actif risqué et d’autre part, augmente la rentabilité de l’actif risqué uniquement pour les agents irrationnels. Par conséquent, les agents rationnels (*arbitrageurs*) vont limiter leurs interventions dans le marché. A terme, seuls les agents irrationnels survivent dans le marché. Il s’ensuit que même à long terme, le prix d’un actif peut être déconnecté de sa valeur
fondamentale. Au niveau empirique, le bruit des agents irrationnels s’illustre par la manipulation des prix de la part des gourous (Rankin (1999), Corsetti, Pesenti et Roubini (2001)), par l’existence de rumeurs (Oberlechner et Hocking (2004)), etc.

Au total, de nombreux faits stylisés sur les marchés financiers s’opposent au fait que le comportement des agents soit conforme au paradigme de l’HAR-HEM. L’orientation de notre recherche se démarque de l’HAR-HEM. Nous supposons que les agents ont une rationalité limitée. L’hypothèse de rationalité limitée (Simon (1955)) suppose que dans la prise de décision, la rationalité des agents est limitée par leur stock d’information, leurs limites cognitives ainsi que par le temps qui leur est imparti pour prendre leurs décisions. L’hypothèse de rationalité limitée ne signifie pas que les agents sont irrationnels voire stupides. L’idée de rationalité limitée est juste plus réaliste que celle défendue par l’HAR-HEM. En effet, la complexité du monde ne permet pas aux individus de connaître le modèle fondamental de détermination du change. Les individus s’appuient plutôt sur des heuristiques pour évaluer le prix d’un actif. Egalement, les capacités cognitives des individus sont trop limitées pour qu’ils puissent tenir compte de l’ensemble de l’information disponible dans le marché, dans leur prise de décision. Les individus vont plutôt sélectionner les informations les plus saillantes et délaisser les autres informations. Par ailleurs, les agents ne sont pas dénués de dimension psychologique comme l’entend l’HAR-HEM. Damasio (2003) montre l’importance des émotions des agents dans le processus de prise de décision des agents.

2.2 ... A la naissance de nouvelles théories de détermination du taux de change

Les limites de l’HAR-HEM ont conduit les chercheurs à rechercher de nouvelles théories de détermination des taux de change. Les chercheurs ont ainsi délaissé le concept d’anticipations homogènes pour celui d’anticipations hétérogènes. L’hétérogénéité des anticipations constitue la base des modèles à flux d’ordre et des modèles comportementaux du change (i.e. les modèles à agents hétérogènes). Egalement, l’hypothèse de rationalité limitée et le fait que les agents font face à un environnement complexe et incertain ont donné lieu à la théorie IKE (Imperfect Knowledge Economics).

Evans et Lyons (2002) ont été les premiers à développer les modèles à flux d’ordre pour la détermination des taux de change. Ces modèles appartiennent au domaine de la microstructure des marchés. Les flux d’ordre se définissent comme le flux net des transactions
d’achat et de vente de devises. Ils représentent donc une mesure de la pression à l’achat net de devises. Les modèles à flux d’ordre supposent que l’information privée a une part plus importante que l’information publique dans la détermination des prix d’actifs. L’information privée contenue dans le flux d’ordre regroupe les anticipations hétérogènes des agents sur la valeur future de l’actif. D’un point de vue empirique, le pouvoir explicatif des modèles à flux d’ordre est supérieur à celui des modèles traditionnels de change. Ce résultat est observé à court terme comme à long terme (Evans et Lyons (2002, 2006, 2008), Berger et al. (2008)). Les modèles à flux d’ordre fournissent également de meilleures prévisions des taux de change que les modèles traditionnels et offrent même de meilleures performances que le modèle de marché aléatoire à court terme (Lindahl et Rime (2006), Rime et al. (2010)). Enfin, les modèles à flux d’ordre proposent également des solutions à l’énigme de la déconnexion des taux de change (Bachetta et van Wincoop (2006), Evans (2010)).


L’approche IKE a été créée par Frydman et Goldberg (2007) et est indépendante tant des modèles basés sur l’HAR-HEM que des modèles à agents hétérogènes. Dans la lignée de la critique de Lucas (1976), Frydman et Goldberg (2007) reconnaissent que les modèles qui prédéterminent les comportements des agents (comme les modèles basés sur l’HAR-HEM et les modèles à agents hétérogènes) sont inappropriés pour modéliser la dynamique du prix d’un actif. En effet, ces modèles assimilent les agents à des robots puisque les agents se

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comportent conformément à des règles exogènes établies par le modélisateur. Ces modèles ne laissent aucune liberté à l’évolution endogène du comportement des agents ainsi qu’à leur environnement. Frydman et Goldberg proposent ainsi de prédéterminer partiellement le comportement des agents en imposant des restrictions qualitatives au lieu d’imposer des contraintes quantitatives. L’approche IKE fournit une nouvelle réponse à l’énigme de la déconnexion des taux de change. Cette approche montre qu’en situation d’incertitude, la déconnexion du change des fondamentaux ne dépend pas du degré de flexibilité des prix comme l’ont précédemment énoncés les modèles basés sur l’HAR-HEM. Ces déconnexions sont plutôt justifiées par la connaissance imparfaite des agents de leur environnement économique.

Au total, les théories s’éloignant du concept de l’HAR-HEM offrent une meilleure compréhension de la dynamique des taux de change. Nous tiendrons ainsi compte dans nos recherches, des enseignements apportés par ces nouvelles théories et plus globalement des enseignements apportés par la finance comportementale.

3. L’amélioration de la structure empirique des modèles traditionnels de change

L’échec empirique des modèles traditionnels de change nous amène à reconsidérer la structure économétrique de ces modèles. Les modèles traditionnels supposent l’existence d’un monde symétrique et s’appuient sur une relation linéaire entre le taux de change et ses fondamentaux. L’hypothèse d’un monde symétrique signifie qu’un choc sur un fondamental dans un pays domestique ou dans un pays étranger aura le même effet sur la dynamique du taux de change. Une structure linéaire signifie qu’il existe une relation stable entre le taux de change et un stock donné de fondamentaux au cours du temps. Ces deux hypothèses ne sont pas vérifiées empiriquement.

En premier lieu, de nombreuses études montrent que les investisseurs réagissent asymétriquement à un choc de nouvelle sur un fondamental entre deux économies (Prast et De Vor (2000), Galati et Ho (2001) et Andersen et al. (2003)). Ainsi, pour le taux de change euro/dollar, les agents semblent surpondérer les nouvelles en provenance des Etats-Unis relativement aux nouvelles en provenance de la zone euro. Ce fait supporte plutôt l’hypothèse d’un monde asymétrique où le taux de change ne réagit pas de la même manière à un même choc sur les fondamentaux domestiques et étrangers.

Jusqu’à maintenant, l’économétrie offre deux types d’outils pour modéliser la dynamique des taux de change à l’aide de modèles non-linéaires. D’un côté, nous avons les modèles non-linéaires où les transitions entre états sont fonctions de variables observables (modèles à seuils et modèles à changement de régime markovien avec probabilités de transition variables dans le temps). D’un autre côté, nous avons des modèles non-linéaires où les transitions entre états sont fonctions de variables inobservables (modèles à changement de régimes markoviens avec probabilités de transition fixes dans le temps).


Les modèles à changement de régime markovien avec probabilités de transition variables dans le temps ont été développés par Diebold et al. (1994), Engel et Hakkio (1994) et Filardo (1994). Dans ces modèles, les transitions entre régimes dépendent d’une variable
d’état observable. Les probabilities de transition entre régimes varient dans le temps en fonction de cette variable d’état observable.

Les modèles à changement de régimes markoviens avec probabilities de transition fixes dans le temps ont été développés par Goldfeld et Quandt (1973) et appliqués aux séries temporelles par Hamilton (1989). Ces modèles diffèrent des modèles à seuils ainsi que des modèles à changement de régime markovien avec probabilities de transition variables dans le temps dans le sens où les probabilities de transition entre états sont ici constantes dans le temps et sont fonctions d’une variable d’état inobservable qui suit généralement une chaîne de Markov d’ordre 1.

Bien que minée par une construction plus ardue relativement aux modèles linéaires, les modèles non-linéaires offrent une structure plus adaptée pour la modélisation de la dynamique des taux de change. En conséquence, notre quête d’un modèle robuste de change s’appuiera sur ce type de modélisation.

4. Problématiques et principaux défis de la thèse

L’objectif de la thèse est de trouver un modèle robuste qui détermine la dynamique des taux de change à court, moyen et long termes. La contrainte imposée est que ce modèle doit fournir des pouvoirs explicatif et prédictif supérieurs à ceux des modèles traditionnels de change.

D’après les arguments mentionnés précédemment, un modèle robuste de détermination des taux de change doit s’écarter du paradigme de l’HAR-HEM. Par conséquent, la construction de nos modèles se base plutôt sur les enseignements de la finance comportementale. Nos modèles tiennent compte non seulement des fondamentaux macroéconomiques mais également des composantes psychologiques et comportementales des agents sur les marchés financiers. Cette voie de recherche est justifiée par l’importance de la prise en compte du comportement des agents pour comprendre la dynamique des taux de change. En effet, les enquêtes menées sur le marché des changes (Cheung et Wong (2000), Cheung et Chinn (2001), Cheung, Chinn et Marsh (2004)) montrent que les comportements des agents tiennent une place majeure dans la détermination des taux de change notamment à court terme (c’est-à-dire pour des horizons inférieurs à 6 mois). La construction de notre modèle tient également compte des enseignements de l’économétrie non-linéaire. Nous utilisons principalement des modèles à changement de régime markovien ainsi que des
modèles à seuils. La difficulté de ce défi réside dans le contournement de ce que Frisch (1970) - le fondateur de l’Econometric Society - nommait la playométrie (playometrics). En d’autres termes, tout modèle mathématique non fondé sur des concepts théoriques pertinents est irrecevable. Par conséquent, notre objectif sera de construire un modèle parcimonieux et robuste de détermination des taux de change, basé sur une théorie économique pertinente.

5. Principaux résultats mis en évidence dans la thèse

Le premier article analyse l’environnement de recherche c’est-à-dire le marché des changes. Le deuxième article fournit des éléments pour comprendre le succès des modèles à flux d’ordre concernant la détermination des taux de change. Le troisième article met en évidence les déterminants des comportements hétérogènes dans le marché des changes. Le quatrième article propose un modèle non conventionnel de détermination du taux de change basé sur les conventions prévalant entre agents sur le marché des changes.

5.1 Les marchés financiers sont-ils efficaces ? L’exemple du marché des changes


L’efficience fondamentale (ou l’efficience au sens de Fama) est vérifiée si d’une part, la dynamique du change reflète celle des fondamentaux et si d’autre part, le ratio rendement/risque associé à une stratégie spéculative ne dépasse pas celui d’une autre stratégie spéculative pour un montant donné de risque. L’efficience spéculative est validée si la spéculaation n’est pas profitable c’est-à-dire si le ratio rendement/risque associé à une stratégie spéculative ne dépasse pas celui d’une autre stratégie spéculative pour un montant donné de risque; et si le taux de change est déconnecté de sa valeur fondamentale. L’efficience macroéconomique décrit la capacité des taux de change à évoluer en accord avec leurs fondamentaux. Cette condition implique non seulement l’existence d’une relation de long terme entre la dynamique du change et celle des fondamentaux mais également la présence de forces de rappel contribuant à réduire les déséquilibres liés aux mouvements du change tels que les déséquilibres de balance commerciale. Un corollaire de la première condition et de la seconde condition est la possibilité de prévoir les taux de change à partir des fondamentaux.
Nous définissons des tests empiriques pour chaque forme d’efficience. L’efficience fondamentale est ainsi vérifiée si la PTINC et l’hypothèse de rationalité des anticipations sont validées dans le marché. Pour évaluer l’efficience spéculative, nous analysons la profitabilité de deux stratégies spéculatives couramment utilisées dans le marché des changes: une stratégie momentum et un carry trade. Concernant l’efficience macroéconomique, nous analysons les pouvoirs explicatifs et prédictifs d’un modèle de change basé sur des fondamentaux macroéconomiques.

Les résultats montrent qu’à court terme (entre 1 mois et 1 an), le marché des changes est purement inefficient. Ce résultat est justifié par le rejet de la PTINC, la possibilité de faire des profits à partir de stratégies momentum et de carry trade ; et également par l’existence de déconnexions entre le taux de change et ses fondamentaux à court terme. A moyen terme (entre 1 an et 2 ans), le marché des changes est spéculativement efficient. En effet, la PTINC est validée, ce qui limite les profits issus du carry trade ; la qualité des prévisions de change basées sur des règles momentum se détériore ce qui limite les profits issus de l’utilisation de règles momentum. A long terme (à partir de 5 ans), l’efficience macroéconomique est vérifiée dans le marché des changes. Les modèles basés sur des fondamentaux ont des pouvoirs explicatif et prédicatif très satisfaisants concernant la dynamique des taux de change. L’efficience fondamentale - l’efficience au sens de Fama - est rejetée quelque soit l’horizon considéré. Ce dernier résultat est justifié par l’échec de la PTINC à court terme (entre 3 mois et 1 an), les piétres performances explicatives et prédictives des modèles fondamentaux à court/moyen termes (entre 1 mois et 2 ans) et le rejet de l’hypothèse de rationalité des anticipations (pour tous les horizons).

L’article montre donc que les modèles traditionnels de change ont de bonnes performances explicatives et prédicatives à long terme (à partir de 5 ans) mais pas à court/moyen termes. Par conséquent, à court/moyen termes, des forces autres que celles fondamentales doivent expliquer la dynamique des taux de change. L’article suggère que la psychologie et le comportement des individus (surréaction, effets mimétiques, rumeurs, etc.) peuvent caractériser ces autres forces. Il s’ensuit qu’un modèle robuste de détermination des taux de change devrait tenir compte non seulement des fondamentaux macroéconomiques mais également de variables comportementales et psychologiques. La littérature économique propose-t-elle déjà un modèle tenant compte de cette composante psychologique (ou comportementale) ?
5.2 Pourquoi les modèles à flux d’ordre sont plus compétitifs que les modèles traditionnels de changes ?

Cet article analyse le succès des modèles à flux d’ordre développés par Lyons (2001) et Evans et Lyons (2002). Les modèles à flux d’ordre fournissent des pouvoirs explicatif et prédicatif supérieurs à ceux des modèles traditionnels de change non seulement à long terme mais également à court terme (Berger et al. (2008)).

Cette différence de performance entre modèles à flux d’ordre et modèles traditionnels de change tient à la prise en compte de deux stocks d’information différents de la part des deux modèles. L’article s’intéresse en conséquence à l’information contenue dans le flux d’ordre.

Nous construisons un modèle théorique qui regroupe l’ensemble des différentes classes d’information disponibles dans le marché des changes et qui sont susceptibles d’affecter le taux de change. L’objectif du modèle est d’observer comment l’information initiale est introduite dans le prix final d’une devise. La structure du modèle se compose d’un modèle à agents hétérogènes et d’un modèle de microstructure.

Trois résultats sont mis en avant. Premièrement, les simulations du modèle répliquent d’importants faits stylisés observés empiriquement sur le marché des changes. A court terme, le taux de change est déconnecté des fondamentaux alors qu’à long terme, il retourne vers sa valeur fondamentale. Les flux d’ordre sont très corrélés à la dynamique du change à court terme comme à long terme. Egalement, l’existence du hot potato effect amplifie le montant des flux d’ordre entre dealers relativement aux flux d’ordre en provenance des clients. Deuxièmement, l’article suggère que le marché des changes est intrinsèquement inefficient. En effet, l’information est déformée à deux niveaux dans le marché. L’information est déformée tant par le bruit lié au comportement des agents que par le bruit de microstructure généré par le mécanisme d’échange intrinsèque au marché des changes. Troisièmement, l’article justifie les meilleures performances empiriques des modèles à flux d’ordre relativement aux modèles traditionnels de change par la considération d’un stock d’information différent entre les deux modèles. Les flux d’ordre contiennent de l’information qui a déjà été traitée par les individus sur le marché. Cette information traitée inclut l’information fondamentale (publique et privée), l’information (publique et privée) liée aux comportements des agents et l’information propre à la microstructure du marché. Inversement, les modèles traditionnels considèrent une information brute, non traitée par les agents ; soit l’information publique sur les fondamentaux du change.
Cet article suggère que les performances des modèles traditionnels de change ne seront jamais supérieures à celles des modèles à flux d’ordre même si des spécifications alternatives sont considérées dans le cadre des modèles traditionnels de change (comme la considération d’une structure non-linéaire entre taux de change et fondamentaux). L’avantage principal des flux d’ordre est de tenir compte intrinsèquement du comportement des agents. Cet article confirme ainsi l’idée sous-jacente au premier article ; soit l’importance de la composante psychologique ou comportementale dans la détermination du taux de change. Les théoriciens des modèles à flux d’ordre sont conscients de la prise en compte des comportements des agents dans les flux d’ordre. Ils affirment que les flux d’ordre approximent les anticipations hétérogènes des agents sur le marché. Cependant, les théoriciens ne modélisent pas l’information contenue dans le flux d’ordre. En conséquence, les modèles à flux d’ordre restent une boîte noire. Ce constat implique qu’en dépit de leur pouvoir explicatif élevé des mouvements du change, les modèles à flux d’ordre ne permettent pas de résoudre l’énigme de la détermination du taux de change puisque les chercheurs ne connaissent pas l’information que recouvre le flux d’ordre. Une voie de recherche permettant de clarifier l’information contenue dans le flux d’ordre consisterait à modéliser les anticipations hétérogènes des agents. Les modèles à agents hétérogènes (Frankel et Froot (1986) et De Grauwe et Grimaldi (2007)) accomplissent cette tâche.

5.3 Une analyse des déterminants des comportements hétérogènes sur les marchés financiers à l’aide de modèles non-linéaires


L’article montre que les modèles à agents hétérogènes expliquent significativement la dynamique des taux de change. Cependant, la littérature n’identifie pas les déterminants des comportements hétérogènes. Ce papier analyse tout d’abord le lien entre comportements hétérogènes dans le marché des changes (pour le taux de change euro/dollar) et dans les marchés boursiers en zone euro et aux Etats-Unis. Ensuite, le papier analyse les déterminants des comportements hétérogènes sur les marchés financiers. La période d’analyse se situe entre janvier 1990 et décembre 2009.
Premièrement, les résultats montrent que l’homogénéité des comportements hétérogènes croît sur la période d’analyse. Ainsi, en début de période, les chocs affectant uniquement le marché des changes ou uniquement les marchés boursiers n’ont pas généré des comportements similaires sur les trois marchés, contrairement aux chocs situés en fin de période. Cette observation suggère une intégration financière croissante entre le marché des changes et les marchés boursiers. Cette intégration augmente le risque d’instabilité financière en période de crise. Par ailleurs, la causalité des comportements est fortement significative entre marchés échangeant un même actif (i.e. entre les marchés boursiers en zone euro et aux Etats-Unis). Inversement, la causalité des comportements est faiblement significative voire non significative entre marchés échangeant deux actifs différents (i.e. entre les marchés boursiers en zone euro ou aux Etats-Unis; et le marché des changes).

Deuxièmement, l’article montre que l’aversión au risque (approximée par la volatilité implicite sur les prix d’option) explique les comportements hétérogènes dans le marché, contrairement aux fondamentaux macroéconomiques. Ainsi, lorsque l’aversión au risque est élevée (faible), les fondamentalistes (chartistes) dominent dans le marché. En conséquence, les fondamentalistes dominent en temps de crise (quand l’aversión au risque augmente) tandis que les chartistes dominent en temps d’expansion économique (lorsque l’aversión au risque est faible). D’un point de vue comportemental, cela signifie que les agents sont plus rationnels en temps de crise (puisqu’ils tiennent compte des fondamentaux pour former leurs anticipations) qu’en temps d’expansion économique (où les agents s’appuient sur des techniques chartistes et ignorent l’information sur les fondamentaux macroéconomiques).

Sur la base de ce fait stylisé, nous construisons une règle de prévision basée sur les comportements des agents. Cette règle fournit de meilleures prévisions en dehors de l’échantillon que le modèle de marche aléatoire. Ce fait est observé à long terme et à court terme. Ce résultat suggère que la prise en compte de faits stylisés sur les comportements des agents est nécessaire à la compréhension et à la prévision de la dynamique des prix d’actifs. Cet article confirme ainsi l’idée défendue dans cette thèse selon laquelle la considération des comportements des agents est importante si l’on désire construire un modèle robuste de détermination des taux de change.

Au-delà de leurs avantages, les modèles à agents hétérogènes présentent deux limites majeures. En premier lieu, ces modèles spécifient arbitrairement une valeur fondamentale du prix de l’actif pour définir la règle fondamentaliste. La spécification d’une valeur unique pour le taux de change fondamental est une limite puisqu’au niveau empirique de multiples valeurs
sont associées à la définition du taux de change fondamental. En second lieu, les modèles à agents hétérogènes prédéterminent entièrement le comportement des agents en associant une règle de comportement exogène à chaque agent. Cette prédétermination des comportements constitue une limite puisqu’au niveau empirique, les agents ont tendance à modifier leurs modèles au cours du temps. La question qui vient naturellement est la suivante: est-il possible de trouver un modèle permettant de tenir compte des changements endogènes dans le comportement des agents ?

5.4 Les conventions dans le marché des changes peuvent-elles expliquer la dynamique des taux de change ?


Dans un premier temps, nous construisons un modèle théorique qui décrit la formation des conventions dans le marché des changes. Le taux de change simulé par le modèle théorique réplique d’importants faits stylisés observés sur la dynamique du change au niveau empirique.

Dans un deuxième temps, nous testons empiriquement le modèle à convention sur le taux de change euro/dollar entre janvier 1995 et décembre 2008. Nous considérons deux approches. En premier lieu, nous utilisons une approche macroéconomique pour mettre en évidence les conventions présentes sur le taux de change euro/dollar. Nous utilisons pour cela les justifications des mouvements de change apportées par le consensus du marché. Dans un
second temps, nous construisons une approche économétrique basée sur l’estimation d’un modèle à coefficients variables dans le temps.

L’analyse macroéconomique et l’approche économétrique débouchent sur les mêmes résultats. Le marché tend à alterner entre des périodes d’optimisme et des périodes de pessimisme. Plus précisément, la dynamique du taux de change euro/dollar est expliquée par l’alternance entre les fondamentaux considérés dans les conventions optimiste et pessimiste. Ce résultat montre l’existence d’une relation non-linéaire entre le taux de change et les fondamentaux macroéconomiques. En d’autres termes, certains fondamentaux sont importants dans la détermination du change pour certaines périodes alors que d’autres fondamentaux sont importants pour d’autres périodes.


Dans un troisième temps, nous comparons les performances prédictives du modèle à convention par rapport à des modélisations alternatives. Les résultats montrent que pour des horizons supérieurs à 1 mois le modèle à convention fournit de meilleures prévisions en dehors de l’échantillon que les modèles traditionnels de change et que la marche aléatoire. Par conséquent, le modèle à convention offre une voie prometteuse pour expliquer et prévoir la dynamique des taux de change.
Article 1

Through the Looking-Glass:
Reconsidering Efficiency in the Foreign Exchange Market

Abstract

This paper argues that market efficiency can be split into multiple and independent forms. We provide three alternative definitions of market efficiency: fundamental efficiency, speculative efficiency and macroeconomic efficiency. We run empirical tests on the euro/dollar, the pound/dollar and the yen/dollar exchange rates. Results show that foreign exchange market efficiency is characterized by pure inefficiency in the short run (between 1 month and 1 year), speculative efficiency in the medium run (between 1 and 2 years) and macroeconomic efficiency in the long run (from 5 years on). Fundamental efficiency - Fama’s definition of efficiency - is rejected at every horizon.

Keywords: Market Efficiency; Fundamental Efficiency; Speculative Efficiency; Macroeconomic Efficiency
Résumé

Ce papier montre que l’efficience des marchés peut être décomposée en des formes multiples et indépendantes. Nous proposons trois définitions de l’efficience informationnelle des marchés: l’efficience fondamentale, l’efficience spéculative et l’efficience macroéconomique. Nous testons ces trois formes d’efficience pour différentes devises et sur différents horizons. Les résultats montrent que le marché des changes est purement inefficient à court terme (entre 1 mois et 1 an), spéculativement efficient à moyen terme (entre 1 an et 2 ans) et macroéconomiquement efficient à long terme (à partir de 5 ans). L’efficience fondamentale - l’efficience au sens de Fama - est rejetée pour tous les horizons.

Mots-clés: Efficience des Marchés; Efficience Fondamentale; Efficience Spéculative; Efficience Macroeconomique
1. Introduction

The analysis of foreign exchange market efficiency has been a long-standing subject for academics and practitioners. Empirical studies have used various strategies to test foreign exchange market efficiency. A lot of tests are based on Fama’s regression (Frankel and Froot (1987), Meredith and Chinn (1998), Ron et al. (2008)); others on the profitability of trading rules (Neely et al. (1997), Burnside et al. (2006, 2008), Park and Irwin (2007), Wagner (2008), Jordà and Taylor (2009)); others on the estimation of equilibrium exchange rate models (Giannellis and Papadopoulos (2009)). After decades of research, the literature has not yet reached a clear-cut conclusion concerning the efficiency of the foreign exchange market. Besides, the concept of efficiency that has been tested across articles may not be identical.

The innovations brought by this paper are twofold. First, we claim that there is not a unique definition of market efficiency but that markets can actually be characterised by multiple and independent forms of efficiency. We come up with three distinct definitions of efficiency (fundamental efficiency, speculative efficiency and macroeconomic efficiency). Secondly, we test which form of efficiency best characterises the foreign exchange market at different time horizons.

We apply empirical tests on three nominal exchange rates: the euro, the pound and the yen against the dollar between January 1998 and December 2008. Results show that several forms of efficiency prevail in the foreign exchange market according to time horizon. The foreign exchange market is thus characterised by pure inefficiency in the short run (between 1 month and 1 year), speculative efficiency in the medium term (between 1 and 2 years) and macroeconomic efficiency in the long run (from 5 years on). Fundamental efficiency is rejected at every horizon.

The remainder of the paper is organized as follows. Starting from the contradiction of Fama (1965)’s efficiency, section 2 defines the different forms of efficiency. Section 3 tests fundamental efficiency by analysing the forecasting abilities of UIP as well as the validation of its underlying hypotheses (risk-neutrality and the rational expectations hypothesis). Section 4 tests speculative efficiency by assessing the profitability of two speculative strategies: a momentum rule and a carry trade strategy. Section 5 tests macroeconomic efficiency by estimating a Behavioral Equilibrium Exchange Rate (BEER) model in order to appraise the

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4 The closest work to this paper is a book chapter by Bourghelle et al. (2005). They discuss several concepts of efficiency but their perspectives remain mostly theoretical. They do not provide any empirically tractable definitions of market efficiency.
explanatory and forecasting powers of macroeconomic fundamentals for exchange rates. Section 6 discusses the results. Section 7 concludes.

2. Reconsidering Fama’s efficient market hypothesis

2.1 The original definition of market efficiency

According to Fama (1965), a market is considered as informationally efficient if the price of an asset is equal to its fundamental value, given all available information. The efficient market hypothesis (EMH) implies that agents are endowed with rational expectations. In other words, agents know the true model of exchange rate determination and are able to compute the fundamental value of the exchange rate.

Assuming risk-neutral agents, Fama’s definition can be formalised in the foreign exchange market by the uncovered interest rate parity (UIP). UIP states that if the interest rate differential between a foreign country and a domestic country is equal to 2 %, then agents will expect an appreciation of the domestic currency by 2 %. Hence:

\[ s_{t+1}^* - s_t = r_t^* - r_t \] (1)

With \( s_{t+1}^* \), the (log of the) expected exchange rate; \( s_t \), the (log of the) current exchange rate; \( (r_t^* - r_t) \), the interest rate differential between the domestic and foreign countries.

UIP ensures that expected returns between an investment in a foreign country and an investment in a domestic country are equal. UIP thus stands in line with Jensen’s (1978) definition of efficiency who claimed that a market is efficient if no profit can be made by speculating in this market. Iterating forward relation (1) leads to:

\[ s_t = s_\infty + \sum_{k=0}^{\infty} (r_{t+k}^* - r_{t+k}) \] (2a)

Exchange rate dynamics are thus explained and predicted by the long run exchange rate \( s_\infty \) and the sum of the expected interest rate differentials. We therefore provide a more
precise definition of Fama’s efficiency. We will refer to this type of efficiency as fundamental efficiency.

**Definition 1:** Fundamental efficiency (or Fama’s efficiency) holds in the foreign exchange market if, on the one hand, exchange rate dynamics reflect the evolution of fundamentals as stated by UIP and on the other hand, if speculation is not profitable in the market; i.e. if the return/risk ratio associated to a speculative strategy is not higher than the one associated to another investment strategy for a given amount of risk.

### 2.2 The contradictions in Fama (1965)’s efficiency

Three contradictions undermine Fama’s efficiency. First, the theory of rational bubble (Blanchard and Watson (1984)) shows that bubbles - disconnections of exchange rates from their fundamental values - can occur even if agents behave rationally. Indeed, by iterating forward the UIP, we get the general form of equation (2a):

\[
\begin{align*}
  s_t = s_{\infty} + \sum_{k=0}^{\infty} \left( r_{t+k} - r^*_{t+k} \right) + b_t \quad \text{with } b_t = E[b_{t+1}]
\end{align*}
\]

(2b)

The value of the exchange rate is split into a fundamental component and a bubble component. Thus in periods of bubble, self-fulfilling expectations by rational agents induce a departure of the exchange rate from its fundamental value although agents are assumed rational. This result goes against the definition of Fama^5.

A second contradiction is illustrated by the paradox of Grossman and Stiglitz (1980). If markets are efficient and information is costly, then rational agents will have no incentive to get any information on the asset. Indeed, in an efficient market, the price of an asset fully reflects all available information. Therefore, if agents behave rationally, they will not pay to get the information since they can freely observe information in quoted prices. Thus if no agent is willing to pay for information concerning an asset, then the price of this asset will not reflect anymore all the available information. The market will not be efficient anymore.

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^5 To rule out the occurrence of rational bubble and insure the convergence towards a particular equilibrium under the EMH, macroeconomic models usually assume that the transversality condition holds: \( \lim_{k \to \infty} b_{t+k} = 0 \).
Consequently, markets have to be at least temporarily inefficient to make the search for information profitable.

Thirdly, testing empirically Fama (1965)'s efficiency (equation (2b)) implies the definition of two models: a model of exchange rate determination to quantify \( s_n \) and a model to determine the future evolution of interest rates to assess \( \sum_{k=0}^{\infty} (r_{t+k} - r_{t+k}^*) \). Neither Fama nor his disciples provide any definition of such models. They further take advantage of this loophole to criticize the results confirming market inefficiency. According to Fama (1991) and his followers, if a model does not validate market efficiency, then this model must be a bad model; i.e. it is not the model considered in the definition of Fama’s efficiency. This “bad model argument” (Fama (1991)) seems however not relevant as it is a general assertion concerning the empirical implementation of economic models.

2.3 Towards new definitions of market efficiency

2.3.1 The speculative efficiency hypothesis

Fundamental efficiency states that no profit can be made from speculation and that exchange rates are always equal to their fundamental value.

If there are many agents with heterogeneous beliefs, the price of an asset may not be equal to its fundamental value, because of noise trading and/or incomplete information (Frankel and Froot (1986), De Long et al. (1990a, 1990b)). In this context, the market can be characterized by inefficiency - the price is not equal to its fundamental value - but may also be efficient in the sense that there may be no profit opportunities.

For example, at short horizons, currency prices are disconnected from their fundamental value (Meese and Rogoff (1983), Chinn et al. (2005)). Speculators can make profits or losses by betting on the chaotic adjustment of the exchange rate towards its fundamental value. Indeed at short horizons, the major part of speculators in the foreign exchange market alternate between periods of profits and periods of losses. Hence Fama’s definition no longer applies since we could have a market were no speculative profits can be made although the exchange rate is not equal to its fundamental value. To address this contradiction, we put forward a new definition of efficiency which we will refer as speculative efficiency:
**Definition 2:** Speculative efficiency prevails in a market if speculation is not profitable; that is if the return/risk ratio associated to a speculative strategy is not higher than the one associated to another investment strategy for a given amount of risk; and if the exchange rate is disconnected from its fundamental value\(^6\).

**2.3.2 The macroeconomic efficiency hypothesis**

Fundamental efficiency assumes risk neutral agents. A lot of studies claim that agents are actually characterised by time-varying risk aversion (Campbell and Cochrane (1999), Kim (2009)). We argue that the time-varying risk aversion of market agents affects the relationship between exchange rates and their fundamentals in the long run. Indeed, time-varying risk aversion affects countries’ risk premia and in turn triggers incentives for countries to reduce their external disequilibria. This process takes time and thus occurs at medium/long run horizons. To take account of the effect of risk aversion on the relationship between exchange rates and fundamentals, we propose an alternative definition of efficiency, which we label macroeconomic efficiency.

**Definition 3:** Macroeconomic efficiency describes the ability of exchange rates to evolve according to their fundamentals. Besides exchange rate dynamics contribute to the reduction of macroeconomic imbalances. Therefore macroeconomic efficiency implies the validation of two conditions in the foreign exchange market: first, the existence of a long run relationship between the exchange rate and its fundamentals; secondly, the existence of correction forces that reduce macroeconomic disequilibria related to exchange rate movements - such as current account deficits. A corollary of the first and second conditions is the possibility to forecast the future dynamics of exchange rates by using macroeconomic fundamentals.

The first and second conditions of macroeconomic efficiency are necessary to ensure markets are able to correct disequilibria appearing after economic shocks. This condition stands in line with the view of Friedman (1953) who advocated that free float regimes induce an automatic correction of external disequilibria at medium/long run horizons. For instance, if an economy in free float is experiencing a current account deficit then its currency will depreciate. This depreciation will increase the competitiveness of the economy and reduce the

\(^6\) Note that this definition of speculative efficiency is totally different from the one proposed by Bilson (1980).
initial deficit. Therefore, exchange rate variations may drive the current account balance towards equilibrium at medium/long run horizons.

The forecasting ability of the model is a correlate of the first and second conditions. Indeed, if exchange rates reflect the information contained in fundamentals in the long run, then such information should improve exchange rate forecasts at least in the long run.

2.4 Towards multiple and distinct forms of market efficiency

The above definitions of market efficiency are distinct from each other.

Speculative efficiency is different from fundamental efficiency. Indeed a market where the value of the exchange rate is fixed by tossing a coin would be efficient in a speculative sense (since expected profits are on average equal to zero) but not efficient in the sense of Fama (since the dynamics of currency prices will not match the evolution of fundamentals; the exchange rate being fixed randomly). The literature always confuses speculative efficiency and fundamental efficiency. For example, Roll (in Roll and Shiller (1992)) argues that “If there’s nothing investors can exploit in a systematic way, […] then it’s very hard to say that information is not being properly incorporated into stock prices”. Roll actually confuses the two types of efficiency. As explained above, if the value of exchange rates is fixed by tossing a coin, then it is on average not possible to make systematic profits in the market although currency prices do not fully reflect all the available information in the market. Thus speculative efficiency is distinct from fundamental efficiency in the sense that speculative efficiency does not necessarily mean that the observed exchange rate is equal to its fundamental value.

Macroeconomic efficiency and fundamental efficiency are also different concepts. Macroeconomic efficiency assumes time-varying risk averse agents while fundamental efficiency assumes risk-neutral agents. Besides fundamental efficiency must be verified at each period of time while macroeconomic efficiency is a long run concept. Formally, macroeconomic efficiency implies that exchange rate misalignments - spreads between the current exchange rate and the long-run exchange rate - exist in the short run but vanish in the medium/long run.

Macroeconomic efficiency is also distinct from speculative efficiency since speculative efficiency assumes the existence of a disconnection of the exchange rate from its fundamental value.
These three distinct definitions of efficiency (fundamental, speculative and macroeconomic) lead to different forms of market efficiency: fundamental efficiency, speculative efficiency, macroeconomic efficiency and pure inefficiency. The literature on market efficiency does not distinguish between these different forms of efficiency. Previous articles only test fundamental efficiency or part of the definition of fundamental efficiency. As a result, we argue that the concept of efficiency that has been tested across previous articles may not be identical.

Having clarified the various forms of efficiency that one can found in a market, we now test which form of efficiency best characterises the foreign exchange market at different time horizons.

3. Testing fundamental efficiency

Tests for fundamental efficiency follow two steps. First we test UIP *ex post*. If UIP and its underlying hypotheses (REH and risk neutrality) hold then fundamental efficiency is validated. On the contrary, if UIP is rejected we then look for the possible reasons behind the rejection of fundamental efficiency. We will focus on the validation of the hypotheses underlying the UIP: risk-neutrality and the rational expectations hypothesis (REH).

Tests for fundamental efficiency are based on the euro/dollar, pound/dollar and yen/dollar exchange rates. The period of analysis spans January 1999 to December 2008. Due to data availability and in accordance with previous studies in the related literature, tests are based on a monthly frequency. The spot and forward rates come from Datastream and the expected exchange rates from Consensus Forecast. Stationarity tests show that the series considered in the models are not stationary and integrated of order 1 over the sample period. Besides cointegration tests show the existence of a significant long run relationship between the endogenous variable and the exogenous variables. We therefore implement our tests by relying on a VECM structure. VECM models are estimated following the method of Johansen and Juselius (1990).
3.1 Testing uncovered interest rate parity *ex post*

Following Frankel and Froot (1987), tests for UIP are based on the analysis of the bias between the forward exchange rate and the future exchange rate\(^8\). If UIP holds, then the constraints \(\alpha = 0\) and \(\beta = 1\) (and \(\varepsilon_{r,k} \sim iidN(\mu,\sigma^2)\)) should be significant in equation (3):

\[
s_{r,k} - s_t = \alpha + \beta(f_{r,k} - s_t) + \varepsilon_{r,k}
\]

We proceed to the estimation of equation (3) by estimating the following VECM:

\[
\begin{align*}
\Delta(s_{r,k} - s_t) &= \lambda_1 \left[(s_{r,k-1} - s_{t-1}) - \alpha - \beta(f_{r,k-1} - s_{t-1})\right] + \sum_{i=1}^{p} \delta_i \Delta(f_{r,k-i} - s_{t-i}) + \sum_{i=1}^{p} \mu_i \Delta(s_{r,k-i} - s_{t-i}) + \varepsilon_{t,1} \\
\Delta(f_{r,k} - s_t) &= \lambda_2 \left[(s_{r,k-1} - s_{t-1}) - \alpha - \beta(f_{r,k-1} - s_{t-1})\right] + \sum_{i=1}^{p} \eta_i \Delta(f_{r,k-i} - s_{t-i}) + \sum_{i=1}^{p} \nu_i \Delta(s_{r,k-i} - s_{t-i}) + \varepsilon_{t,2}
\end{align*}
\]

UIP holds if the Likelihood Ratio test verifies the following constraints: \(\alpha = 0\) and \(\beta = 1\) in the long run relationship.

\[
\text{Table 1: Results for UIP tests at 3 months, 1 year and 2 years}
\]

<table>
<thead>
<tr>
<th>(s_t)</th>
<th>Horizon</th>
<th>(\lambda)</th>
<th>(\alpha)</th>
<th>(\beta)</th>
<th>R2adj</th>
<th>White</th>
<th>LM</th>
<th>J&amp;B</th>
<th>(\beta = 1)</th>
<th>(\alpha = 0, \beta = 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euro</td>
<td>3</td>
<td>-0.30 ([-2.59])</td>
<td>6.3x10(^{-3}) ([0.83])</td>
<td>-4.63 ([-2.39])</td>
<td>0.33</td>
<td>76.03 ((0.18))</td>
<td>3.40 ((0.49))</td>
<td>4.30 ((0.36))</td>
<td>4.17 ((0.04))</td>
<td>3.64 ((0.05))</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>-0.10 ([-2.01])</td>
<td>0.05 ([2.11])</td>
<td>-5.63 ([-3.10])</td>
<td>0.04</td>
<td>42.50 ((0.44))</td>
<td>3.15 ((0.53))</td>
<td>4.23 ((0.37))</td>
<td>4.91 ((0.02))</td>
<td>4.18 ((0.04))</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>-0.30 ([-2.70])</td>
<td>0.06 ([2.31])</td>
<td>2.11 ([1.96])</td>
<td>0.22</td>
<td>17.13 ((0.51))</td>
<td>8.77 ((0.06))</td>
<td>3.27 ((0.51))</td>
<td>1.62 ((0.20))</td>
<td>1.27 ((0.25))</td>
</tr>
<tr>
<td>Pound</td>
<td>3</td>
<td>-0.45 ([-4.96])</td>
<td>-3.3x10(^{-3}) ([-0.46])</td>
<td>-2.82 ([-1.82])</td>
<td>0.18</td>
<td>23.02 ((0.81))</td>
<td>4.48 ((0.34))</td>
<td>4.27 ((0.37))</td>
<td>4.90 ((0.02))</td>
<td>6.69 ((0.00))</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>-0.10 ([-2.13])</td>
<td>-0.03 ([-1.42])</td>
<td>-5.26 ([-3.16])</td>
<td>0.03</td>
<td>64.74 ((0.85))</td>
<td>18.72 ((0.00))</td>
<td>7.69 ((0.10))</td>
<td>8.19 ((0.00))</td>
<td>7.68 ((0.00))</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>-0.41 ([-3.86])</td>
<td>0.20 ([8.73])</td>
<td>2.86 ([4.74])</td>
<td>0.32</td>
<td>31.64 ((0.38))</td>
<td>4.05 ((0.39))</td>
<td>5.97 ((0.20))</td>
<td>0.56 ((0.45))</td>
<td>1.24 ((0.26))</td>
</tr>
<tr>
<td>Yen</td>
<td>3</td>
<td>-0.49 ([-4.74])</td>
<td>-0.02 ([-1.62])</td>
<td>-2.02 ([-1.62])</td>
<td>0.37</td>
<td>78.21 ((0.14))</td>
<td>0.42 ((0.98))</td>
<td>5.35 ((0.25))</td>
<td>4.89 ((0.02))</td>
<td>3.12 ((0.07))</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>-0.21 ([-3.43])</td>
<td>-0.09 ([-2.28])</td>
<td>-3.01 ([-2.94])</td>
<td>0.12</td>
<td>35.09 ((0.76))</td>
<td>3.73 ((0.44))</td>
<td>4.70 ((0.31))</td>
<td>7.13 ((0.00))</td>
<td>4.90 ((0.02))</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>-0.17 ([-2.28])</td>
<td>0.32 ([2.00])</td>
<td>4.81 ([2.00])</td>
<td>0.07</td>
<td>32.68 ((0.33))</td>
<td>4.62 ((0.32))</td>
<td>3.14 ((0.31))</td>
<td>0.31 ((0.57))</td>
<td>0.23 ((0.62))</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; *p-values* are mentioned in brackets; critical values for the test of Student amount to 1.96 at a 5% confidence level and to 1.64 at a 10% confidence level; 5 lags are considered for the LM test.

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\(^7\) See appendix D.

\(^8\) See appendix B.
Diagnostic tests in table 1 show no sign of heteroskedasticity (White test) and autocorrelation in the residuals (LM test). However, residuals do not follow a normal distribution (Jarque and Bera test).

Table 1 shows that at short horizons (3 and 12 months) UIP is rejected. The coefficients $\beta$ are significant and negative; the constraints $\alpha = 0$ and $\beta = 1$ are not accepted in the long run relationship. On the contrary for medium/long run horizons (2 years), UIP holds significantly. The coefficients $\beta$ are significant and positive and the constraints $\alpha = 0$ and $\beta = 1$ are not rejected in the long run relationship.

Previously, Meredith and Chinn (1998) tested UIP based on the interest rate differential (relation (1)) at different horizons (3, 6 and 12 months, 5 years and 10 years). They show that UIP holds for long run horizons (for 5 and 10 years). Results show here that UIP holds also for medium horizons (2 years).

The failure of UIP in the short run can be attributed to two factors: a possible bias in equation (3) due to the assumption of risk neutral agents (i.e. the exclusion of a risk premium) instead of risk averse agents; and/or the rejection of REH - we assume in equation (3) that agents behave rationally. In order to find the factors justifying the failure of UIP at short horizons, we test whether the hypotheses of risk-neutrality and rational expectations hold in the market.

### 3.2 Tests for time-varying risk aversion

The failure of UIP in the short run (also known as the forward bias) can be caused by the assumption of risk-neutral agents (Frankel and Froot (1987), Sarno and Taylor (2002)). We thus test whether the failure of UIP is due to the omission of a time-varying risk premium. We regress the variation of the expected exchange rate ($s_{t+k}^{a} - s_t$) on the forward premium ($f_{t,k} - s_t$):

$$s_{t+k}^{a} - s_t = \alpha + \beta(f_{t,k} - s_t) + \varepsilon_{t+k} \tag{4}$$

---

$^9$ See appendix B.
In a VECM form, equation (4) becomes:

\[
\begin{align*}
\Delta(s_{t+k} - s_t) &= \lambda_1 \left[ (s_{t+k-1}^a - s_{t-1}) - \alpha - \beta (f_{t,k-1} - s_{t-1}) \right] + \sum_{i=1}^{p} \delta_i \Delta(f_{t,k-i} - s_{t-i}) + \sum_{i=1}^{p} \mu_i \Delta(s_{t+k-i}^a - s_{t-i}) + \varepsilon_{t,1} \\
\Delta(f_{t,k} - s_t) &= \lambda_2 \left[ (s_{t+k-1}^a - s_{t-1}) - \alpha - \beta (f_{t,k-1} - s_{t-1}) \right] + \sum_{i=1}^{p} \eta_i \Delta(f_{t,k-i} - s_{t-i}) + \sum_{i=1}^{p} \nu_i \Delta(s_{t+k-i}^a - s_{t-i}) + \varepsilon_{t,2}
\end{align*}
\]

Following Frankel and Froot (1987), three tests are applied on the model. First, if the constraints \( \alpha = 0 \) and \( \beta = 1 \) hold then the forward bias is explained only by systematic expectation errors and not by a time-varying risk premium. Secondly, if the constraint \( \beta = 1 \) is verified then a risk premium explains part of the forward bias. Thirdly, if \( \beta = 0.5 \) then the forward bias is equally explained by the presence of a time-varying risk premium and systematic expectation errors\(^{11}\). Table 2 presents the results.

### Table 2: Results for a time-varying risk premium at 3 months, 1 year and 2 years

<table>
<thead>
<tr>
<th>( s_t )</th>
<th>Horizon</th>
<th>( \lambda )</th>
<th>( \alpha )</th>
<th>( \beta )</th>
<th>( R^2a )</th>
<th>White</th>
<th>LM</th>
<th>J&amp;B</th>
<th>( \beta = 0.5 )</th>
<th>( \beta = 1 )</th>
<th>( \alpha = 0, \beta = 1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euro</td>
<td>3</td>
<td>0.01</td>
<td>2.58</td>
<td>0.24</td>
<td>34.74</td>
<td>7.45</td>
<td>6.01</td>
<td>2.07</td>
<td>1.30</td>
<td>3.78</td>
<td></td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.01</td>
<td>2.58</td>
<td>0.24</td>
<td>38.95</td>
<td>6.49</td>
<td>6.88</td>
<td>0.49</td>
<td>5.96</td>
<td>6.38</td>
<td></td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>0.01</td>
<td>2.58</td>
<td>0.24</td>
<td>30.44</td>
<td>4.54</td>
<td>5.15</td>
<td>5.22</td>
<td>4.32</td>
<td>10.11</td>
<td></td>
</tr>
<tr>
<td>Pound</td>
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<td>0.21</td>
<td>2.64</td>
<td>0.51</td>
<td>98.94</td>
<td>4.90</td>
<td>4.90</td>
<td>2.32</td>
<td>0.21</td>
<td>4.63</td>
<td></td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.21</td>
<td>2.64</td>
<td>0.51</td>
<td>20.27</td>
<td>1.80</td>
<td>3.07</td>
<td>3.07</td>
<td>0.21</td>
<td>4.71</td>
<td></td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>0.21</td>
<td>2.64</td>
<td>0.51</td>
<td>24.29</td>
<td>1.80</td>
<td>3.66</td>
<td>6.79</td>
<td>6.19</td>
<td>6.89</td>
<td></td>
</tr>
<tr>
<td>Yen</td>
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<td>2.58</td>
<td>0.24</td>
<td>26.27</td>
<td>1.46</td>
<td>5.77</td>
<td>0.96</td>
<td>1.44</td>
<td>4.90</td>
<td></td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>0.01</td>
<td>2.58</td>
<td>0.24</td>
<td>53.66</td>
<td>5.10</td>
<td>4.91</td>
<td>3.50</td>
<td>1.85</td>
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<tr>
<td></td>
<td>24</td>
<td>0.01</td>
<td>2.58</td>
<td>0.24</td>
<td>15.82</td>
<td>6.49</td>
<td>4.66</td>
<td>4.32</td>
<td>4.23</td>
<td>4.31</td>
<td></td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; \( p \)-values are mentioned in brackets; critical values for the test of Student amount to 1.96 at a 5 % confidence level and to 1.64 at a 10 % confidence level; 5 lags are considered in the LM test.

Diagnostic tests show no sign of heteroskedasticity and autocorrelation in the residuals; and residuals are normally distributed.

\(^{10}\) See appendix C. Expected exchange rates come from Consensus Forecast. Consensus Forecast asks a panel of economists (mostly fundamentalist economists) to provide their expectations on the future realisations of currency prices at 3 months, 1 year and 2 years.

\(^{11}\) Appendix C provides elements to understand the theoretical relevance of such constraints.
The first hypothesis ($\alpha = 0$ and $\beta = 1$) is rejected for every currency. Thus the forward bias is not entirely explained by systematic expectation errors. The second hypothesis ($\beta = 1$) is accepted for every currency at short horizons (shorter than 2 years) but rejected at horizons equal to 2 years. Thus a risk premium explains part of the forward bias at horizons shorter than 2 years where $p$-values are very high (table 2, column 11). This result casts doubts on the specification of the test for UIP (equation (3)) and also about the robustness of the rejection of UIP at short run horizons (less than 2 years). The third hypothesis ($\beta = 0.5$) is accepted for every currency at short run horizons (from 3 to 12 months) and rejected for horizons equal to 2 years. Thus, the forward bias is equally explained by a time-varying risk premium and systematic errors at short horizons. Conversely, for long run horizons (longer than 2 years), the forward bias is explained more by systematic expectation errors and less by a time-varying risk premium. Indeed $p$-values are very low at such horizons for the euro and the pound (table 2, column 10).

Thus, the rejection of UIP in the short run (from 3 to 12 months) can be attributed to the omission of a time-varying risk premium in equation (3). The possible misspecification of equation (3) casts doubts on the failure of UIP in the short run and hence on the possible rejection of fundamental efficiency. To counter the uncertainty concerning the validation of fundamental efficiency, we test the second underlying hypothesis of UIP: the rational expectations hypothesis (REH).

### 3.3 Tests for the rational expectations hypothesis

Following Frankel and Froot (1987), the test for the rational expectations hypothesis is based on the following relationship\(^\text{12}\):

\[
s_{t+k} - s_t = \alpha + \beta(s_{t+k}^a - s_t) + \epsilon_{t+k}
\]

\(^\text{12}\) See appendix B.
In a VECM form, equation (5) becomes:

\[
\begin{align*}
\Delta(s_{t+k} - s_t) &= \lambda_1 [(s_{t+k-1} - s_{t-1}) - \alpha - \beta(s_{t+k-1} - s_{t-1})] + \sum_{i=1}^{p} \delta_i \Delta(s_{t+k-i} - s_{t-i}) + \sum_{i=1}^{p} \mu_i \Delta(s_{t+k-i} - s_{t-i}) + \varepsilon_{t,i} \\
\Delta(s_{t+k} - s_t) &= \lambda_2 [(s_{t+k-1} - s_{t-1}) - \alpha - \beta(s_{t+k-1} - s_{t-1})] + \sum_{i=1}^{p} \eta_i \Delta(s_{t+k-i} - s_{t-i}) + \sum_{i=1}^{p} \nu_i \Delta(s_{t+k-i} - s_{t-i}) + \varepsilon_{t,i}
\end{align*}
\]

REH holds if expectation errors are not systematic i.e. if the constraints \( \alpha = 0 \) and \( \beta = 1 \) (and \( \varepsilon_{t+k} \rightarrow iidN(\mu, \sigma^2) \)) are significant in the model.

Table 3: Results for the test of the REH at 3 months, 1 year and 2 years

<table>
<thead>
<tr>
<th>s_t</th>
<th>Horizon</th>
<th>( \lambda )</th>
<th>( \alpha )</th>
<th>( \beta )</th>
<th>R2adj</th>
<th>White</th>
<th>LM</th>
<th>J&amp;B</th>
<th>( \beta = 1 )</th>
<th>( \alpha = 0, \beta = 1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>-0.49</td>
<td>-0.01</td>
<td>-0.74</td>
<td>0.19</td>
<td>45.01</td>
<td>8.84</td>
<td>3.01</td>
<td>7.69</td>
<td>6.50</td>
</tr>
<tr>
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<td>[-1.82]</td>
<td>[-1.86]</td>
<td></td>
<td>(0.03)</td>
<td>(0.06)</td>
<td>(0.55)</td>
<td>(0.00)</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>-0.07</td>
<td>0.10</td>
<td>-1.82</td>
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<td>12.74</td>
<td>3.87</td>
<td>1.98</td>
<td>11.17</td>
<td>4.12</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>-0.04</td>
<td>0.16</td>
<td>-1.54</td>
<td>0.03</td>
<td>50.39</td>
<td>0.90</td>
<td>1.12</td>
<td>7.54</td>
<td>10.52</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>(0.80)</td>
<td>(0.42)</td>
<td>(0.73)</td>
<td>(0.00)</td>
<td>(0.04)</td>
</tr>
<tr>
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<td>(0.92)</td>
<td>(0.88)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>-0.43</td>
<td>6.0x10^{-3}</td>
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<td>0.17</td>
<td>27.81</td>
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<td>6.71</td>
</tr>
<tr>
<td></td>
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<td></td>
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<td>(0.68)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
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<td>6.31</td>
<td>4.07</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>-0.07</td>
<td>0.059</td>
<td>-2.68</td>
<td>0.17</td>
<td>139.49</td>
<td>2.91</td>
<td>12.64</td>
<td>5.76</td>
<td>6.75</td>
</tr>
<tr>
<td></td>
<td>[-2.12]</td>
<td>[1.80]</td>
<td>[-1.85]</td>
<td></td>
<td></td>
<td>(0.05)</td>
<td>(0.57)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[-1.91]</td>
<td>[1.66]</td>
<td></td>
<td></td>
<td>(0.66)</td>
<td>(0.24)</td>
<td>(0.28)</td>
<td>(0.01)</td>
<td>(0.04)</td>
</tr>
<tr>
<td></td>
<td>3</td>
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<td>-9.9x10^{-3}</td>
<td>-0.61</td>
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<td>27.58</td>
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<td>9.02</td>
<td>7.71</td>
</tr>
<tr>
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<td>[-5.24]</td>
<td>[-1.16]</td>
<td>[-1.64]</td>
<td></td>
<td></td>
<td>(0.06)</td>
<td>(0.03)</td>
<td>(0.45)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>12</td>
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<td>0.06</td>
<td>-2.02</td>
<td>0.03</td>
<td>15.99</td>
<td>3.14</td>
<td>4.85</td>
<td>4.25</td>
<td>3.45</td>
</tr>
<tr>
<td></td>
<td>[-2.01]</td>
<td>[1.72]</td>
<td>[-2.43]</td>
<td></td>
<td></td>
<td>(0.59)</td>
<td>(0.53)</td>
<td>(0.30)</td>
<td>(0.03)</td>
<td>(0.06)</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>-0.08</td>
<td>3.0x10^{-4}</td>
<td>1.88</td>
<td>0.15</td>
<td>79.68</td>
<td>7.54</td>
<td>12.67</td>
<td>3.44</td>
<td>4.67</td>
</tr>
<tr>
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<td>[-2.56]</td>
<td>[0.00]</td>
<td>[1.40]</td>
<td></td>
<td></td>
<td>(0.95)</td>
<td>(0.10)</td>
<td>(0.01)</td>
<td>(0.06)</td>
<td>(0.03)</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; p-values are mentioned in brackets; critical values for the test of Student amount to 1.96 at a 5 % confidence level and to 1.64 at a 10 % confidence level.

Diagnostic tests show no heteroskedasticity in the residuals for the pound and the yen contrary to the euro. Autocorrelation in the residuals is not significant for every currency at 12 months and 24 months; but significant for the pound and the yen at 3 months. Residuals follow a normal distribution except for the pound and the yen at 24 months.

Table 3 shows that the REH is significantly rejected for all currencies at all horizons. Indeed, for short run horizons (3 months and 1 year) as well as for medium/long run horizons (2 years), coefficients are strongly negative and significant (see also appendix A). Such results imply that when agents expect an appreciation of the exchange rate at time \( t+k \) (with \( k = 3, 12 \) and 24), the price of the currency actually depreciates in \( t+k \) ! Therefore, the rejection of the REH clears the ambiguity on the robustness of the failure of UIP in the short run, and furthermore on the rejection of fundamental efficiency.
3.4 Discussion of the results

Tests show that UIP holds in the long run but not in the short run. Besides, REH is rejected at all horizons. As fundamental efficiency implies the verification of UIP and REH, fundamental efficiency does not hold in the foreign exchange market for every horizon.

Several reasons explain the rejection of UIP in the short run and the rejection of REH for every horizon. Systematic errors by agents can be attributed to the heterogeneity of agents’ expectations. Indeed, the sample of agents’ expectations considered here - Consensus Forecast - may not finely represent the expectations of the whole market. Consensus Forecast regroups mostly fundamentalist economists. However in the short run, market agents are in majority chartist (Allen and Taylor (1992), Cheung and Chinn (2001)). Fundamentalists dominate the market only in the long run. The strong heterogeneity in exchange rate expectations in the short run between Consensus Forecast and the whole market could explain the failure of UIP in the short run. In the long run, as agents become more fundamentalist, agents’ expectations from Consensus Forecast reflect more properly market expectations. This fact may explain the validation of UIP in the long run. Causality can however run the other way round. Because it is difficult to predict exchange rates at long run horizons, the farther the horizon, the more economists from Consensus Forecast will rely on forward exchange rates to predict future exchange rates. Thus this fact may also explain the validation of UIP in the long run. Besides, given the fact that economists from Consensus Forecast do not trade directly in the market, they may face a different stock of information compared to agents who trade directly in the foreign exchange market. This difference in the stock of information could also explain the failure of UIP in the short run. In spite of the limits concerning the sample of Consensus Forecast, our results seem rather robust. Indeed, the analysis of market agents’ expectations by Bizimana (2008) based on a Reuters survey leads to the same conclusion.

4. Testing speculative efficiency

To test speculative efficiency we analyse whether speculation is profitable in the foreign exchange market. We rely on two speculative strategies commonly used by agents who speculate in the foreign exchange market: a momentum rule and a carry trade.

We first test the profitability of a momentum rule on the euro/dollar, pound/dollar and yen/dollar exchange rates. In accordance with previous studies in the related literature
(Schulmeister (2008)), we rely on a daily frequency. We then test the profitability of carry trades on the dollar/yen, euro/yen and pound/yen. Following Burnside et al. (2006, 2008) we rely on a quarterly frequency for the carry trade. We however test whether results are sensitive to the chosen frequencies. For both tests the period of analysis spans January 1998 to December 2008.

4.1 Are momentum rules profitable in the foreign exchange market?

We analyse the profitability of a momentum rule in the foreign exchange market. A momentum rule is a chartist strategy that aims at forecasting exchange rates based on the difference between two moving average series:

\[ \Delta s_{t+1}^a = ma_{t}^u - ma_{t}^l \]  

(6)

With \( ma_{t}^u = \frac{\sum_{k=0}^{N_a} s_{t-k}}{N_{st}} \) and \( ma_{t}^l = \frac{\sum_{k=0}^{N_a} s_{t-k}}{N_{lt}} \) where \( N_{st} < N_{lt} \) and \( N \) stands for the number of days.

The momentum rule works as follows: if the price of the currency has appreciated in the past \( (ma_{t+1}^u > ma_{t+1}^l) \) then agents will expect an appreciation of the price of the currency (and conversely if \( ma_{t+1}^u < ma_{t+1}^l \)). We thus invest in euros in \( t+1 \) if \( ma_{t+1}^u > ma_{t+1}^l \). We then hold the position until \( ma_{t+1}^u < ma_{t+1}^l \) where the position is closed at \( t + k + 1 \).

Tests are carried out for different \( N \) (with \( N_{st} < N_{lt} \)). Rules’ profitability changes among years but results remain globally the same over the sample period. We here mention the results for \( N_{st} = 14 \) days and \( N_{lt} = 200 \) days. Returns of momentum strategies are compared to those offered by a buy-and-hold strategy on the S&P500 and risk-free strategies (on 3-months bills and 10-years bonds) in the United States. Table 4 reports the returns associated to each strategy.

13 Changes in data frequency do not alter the final result concerning the tests for speculative efficiency. Results are available upon author request.

14 Annual returns \( R \) are computed as follows: \( R = \frac{1}{N} \sum_{i=1}^{N} R_i \), with \( R_i \) the daily returns associated to an open position based on a momentum rule; \( N \), the number of open positions taken in the foreign exchange market.
Table 4: Annual average returns of a momentum strategy, a buy-and-hold strategy (B&H) and a risk-free strategy

<table>
<thead>
<tr>
<th>Periods</th>
<th>Strategies</th>
<th>MM €/$</th>
<th>MM £/$</th>
<th>MM Y/$</th>
<th>B&amp;H US T-Bill 3 months</th>
<th>US T-Bonds 10 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td></td>
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<td>1.90</td>
<td>5.43</td>
<td>26.31</td>
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</tr>
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<td>-16.49</td>
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</tr>
<tr>
<td>2006</td>
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<td>27.28</td>
<td>-0.80</td>
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<td>4.15</td>
</tr>
<tr>
<td>2007</td>
<td></td>
<td>15.90</td>
<td>2.78</td>
<td>5.88</td>
<td>14.79</td>
<td>4.95</td>
</tr>
<tr>
<td>2008</td>
<td></td>
<td>-11.51</td>
<td>-15.54</td>
<td>25.69</td>
<td>-15.69</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>Annual Average Return</th>
<th>Maximal Return</th>
<th>Minimum Return</th>
<th>Standard Deviation</th>
<th>Sharpe Ratio</th>
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<td>3.18</td>
<td>5.88</td>
<td>3.60</td>
<td>4.74</td>
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<td>25.48</td>
<td>27.28</td>
<td>25.69</td>
<td>26.31</td>
<td>5.46</td>
<td>6.34</td>
</tr>
<tr>
<td>-16.65</td>
<td>-20.12</td>
<td>-11.94</td>
<td>-15.69</td>
<td>1.06</td>
<td>3.64</td>
</tr>
<tr>
<td>14.66</td>
<td>15.19</td>
<td>10.65</td>
<td>14.96</td>
<td>1.58</td>
<td>0.68</td>
</tr>
<tr>
<td>-0.02</td>
<td>-0.10</td>
<td>-0.04</td>
<td>-0.02</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NB: Sharpe ratio are defined as the ratio of the return difference between a speculative strategy and a risk-free strategy (US Treasury-bill) at 3 months over the risk associated with the speculative strategy; all returns are expressed in US dollars.

Returns generated by the momentum rule vary across currencies and across periods. The momentum rule offers high returns for particular periods (between January 2002 and December 2004 for the euro and the pound) and low returns at other periods (between January 1999 and December 2001 for the euro and the pound). Globally, the return/risk ratios associated to the chartist rule are lower than those offered by alternative investment strategies (such as an investment in US Treasury bills). The same results are obtained with other momentum rules with different number of days\(^\text{15}\). Hence table 4 shows that momentum rules can be profitable in the short run, while in the long run, profits opportunities converge on average to zero. These results imply that speculative efficiency is verified in the short run but not in the long run.

4.2 Do carry trade strategies generate profits?

The carry trade is a speculative strategy where investors borrow from low-yielding currencies to invest in high-yielding currencies. According to UIP, carry trades should not yield any profits. Indeed, UIP states that expected returns between a foreign and a domestic investment are equal since the variations in the expected exchange rate should compensate

\(^{15}\) Results are available upon author request.
any return differentials between two countries. However, the failure of UIP highlighted in section 3.1 implies that carry trade strategies may be profitable.

Assuming a carry trade between the United States and Japan, the speculative strategy works as follows: given that Japanese interest rates are lower than US interest rates ($R_{t-1} < R^*_{t-1}$) over the sample period, a carry trade strategy involves borrowing in Japan at the rate $R_t$ and investing in the United States at the rate $R^*_{t-1}$. Profits induced by this operation are given by:

$$\pi_t = \frac{S_t}{S_{t-1}}(1+R^*_{t-1}) - (1+R_{t-1})$$  \hspace{1cm} (7)

With $S_t$, the dollar/yen exchange rate (listed as $S$ yen per one dollar); $R^*_{t-1}$ and $R_{t-1}$, respectively, the interbank interest rate at 3 months in the United States and in Japan.

Table 5: Cumulated annual average returns of a carry trade strategy, a buy-and-hold strategy ($B&H$) and a risk-free strategy

<table>
<thead>
<tr>
<th>Periods</th>
<th>Strategies</th>
<th>US T-Bill 3 months</th>
<th>US T-Bonds 10 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>3,02</td>
<td>11,78</td>
<td>4,33</td>
</tr>
<tr>
<td>1999</td>
<td>-12,52</td>
<td>5,76</td>
<td>8,44</td>
</tr>
<tr>
<td>2000</td>
<td>16,72</td>
<td>27,29</td>
<td>39,67</td>
</tr>
<tr>
<td>2001</td>
<td>20,45</td>
<td>26,04</td>
<td>24,99</td>
</tr>
<tr>
<td>2002</td>
<td>15,41</td>
<td>13,44</td>
<td>-2,11</td>
</tr>
<tr>
<td>2003</td>
<td>16,67</td>
<td>13,70</td>
<td>-4,61</td>
</tr>
<tr>
<td>2004</td>
<td>11,37</td>
<td>23,81</td>
<td>4,89</td>
</tr>
<tr>
<td>2005</td>
<td>8,75</td>
<td>19,49</td>
<td>24,22</td>
</tr>
<tr>
<td>2006</td>
<td>20,57</td>
<td>30,58</td>
<td>18,29</td>
</tr>
<tr>
<td>2007</td>
<td>14,71</td>
<td>14,56</td>
<td>12,39</td>
</tr>
<tr>
<td>2008</td>
<td>-11,26</td>
<td>-32,54</td>
<td>-15,24</td>
</tr>
<tr>
<td>Annual Average Return</td>
<td>9,45</td>
<td>13,99</td>
<td>10,48</td>
</tr>
<tr>
<td>Maximal Return</td>
<td>20,57</td>
<td>30,58</td>
<td>39,67</td>
</tr>
<tr>
<td>Minimum Return</td>
<td>-11,26</td>
<td>-32,54</td>
<td>-15,24</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>12,41</td>
<td>17,09</td>
<td>16,42</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0,68</td>
<td>0,83</td>
<td>0,58</td>
</tr>
</tbody>
</table>

NB : Sharpe ratio are defined as the ratio of the return difference between a speculative strategy and a risk-free strategy (US Treasury-bill) at 3 months over the risk associated with the speculative strategy; all returns are expressed in US dollars.

For each currency, returns offered by carry trades are relatively high between January 1998 and December 2007. Returns become negative at the end of the period (between January 2008 and December 2008). This fact is due to the appreciation of the yen and the fall of

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16 Annual cumulated returns $R$ are computed as follows: $R = \prod_{t=1}^{4} (1+ R_t) - 1$. 
interest rates in the United States, the United Kingdom and the Euro zone during the subprime crisis. However, carry trades offer globally higher return/risk ratios than passive investment on the S&P500 or risk-free investments. Therefore, carry trades appear globally profitable over the sample period. These results corroborate the failure of UIP in the short run (table 1). As observed with the momentum rule, there are some periods in which carry trades are profitable while at other periods they generate losses. Hence table 5 suggests that in the short run, profits from carry trades are likely while in the long run, profits converge on average to zero. These results imply that speculative efficiency is verified in the short run but not in the long run. There is however an important difference between the carry trade and the momentum strategy. The definition of the long term associated to both strategies cannot be the same. The long run of an investment strategy depends on the adjustment delay of its underlying variables (macroeconomic variables for carry trades and the exchange rate for momentum rules). In the case of a momentum strategy, the adjustment is defined as the mean reversion of the observed exchange rate towards its moving average. Conversely, in the carry trade, the adjustment is illustrated not solely by interest rate variations but also by the return of the observed exchange rate towards its fundamental value. The delay of adjustment - the mean reversion - lasts longer for macroeconomic fundamentals than for the exchange rate itself. As a result, considering a short period - short enough to avoid adjustments in the underlying variables of an investment strategy - may produce higher Sharpe ratios. As adjustments of the variables related to the carry trade (i.e. interest rates) last longer than adjustments of the underlying variables for the momentum strategy (i.e. exchange rate), we end up with higher Sharpe ratios for the carry trade than for the momentum strategy. Had we considered longer periods - long enough to allow for adjustments in macroeconomic variables - we would have found lower Sharpe ratios for the carry trade. To justify this point, we cite Burnside et al. (2006) and Jordà and Taylor (2009) who analysed the profitability of carry trade strategies on longer periods and found lower Sharpe ratios. Also and in line with our previous statements, Jordà and Taylor (2009) and Nozaki (2010) justify that low Sharpe ratios related to carry trades are due to the occurrence of exchange rates adjustments towards their fundamental value in their respective (long) sample periods.
4.3 Discussion of the results

Empirical results show that momentum and carry trade strategies are profitable in the short run but not in the long run. Therefore, speculative efficiency does not hold in the short run but is verified in the long run.

A possible factor justifying speculation gains in the short run lies in the fact that winning speculators use information more efficiently than losing speculators or that winning speculators have an informational advantage over losing speculators. Nowadays, every investor in the market has access to a wide range of information about macroeconomic fundamentals through software such as Bloomberg, Reuters, etc. As a result, it is less likely that profits from speculative strategies are determined by informational advantages on macroeconomic fundamentals. We argue that winning strategies may take account of a key component of exchange rate beyond macroeconomic fundamentals. In the short run, this component could be market agents’ behaviours. Indeed, according to surveys among financial practitioners (Cheung and Wong (2000), Cheung and Chinn (2001), Cheung, Chinn and Marsh (2004)), agents’ behaviours play a major role in the determination of exchange rates at short run horizons (from intraday frequencies to 6 months). Thus a fine appraisal of agents’ behaviours could explain the profits of speculators in the short run. Studies from Osler (2003) and Gehrig and Menkhoff (2003) show evidence of significant links between chartism and market agents’ behaviours. Further the high volatility of profits with the momentum rule (table 4) relative to profits obtained with the carry trade strategy (table 5) could thus be explained by two factors: the fact that market agents’ behaviours is a highly volatile component of exchange rates; and the fact that chartism (momentum rules) provides information about market agents’ behaviours contrary to models based on macroeconomic fundamentals (carry trades).

5. Empirical tests for macroeconomic efficiency

5.1 Testing the first and second conditions of macroeconomic efficiency

Testing the first condition of macroeconomic efficiency requires testing the existence of a long run relationship between the exchange rate and its fundamentals and also taking account of the time-varying risk aversion of agents in the market. We thus estimate a portfolio model of exchange rate based on a BEER model (Clark and MacDonald (1998)). The flexible
framework of BEER models enables us to estimate a dynamic relationship between the exchange rate and its fundamentals\textsuperscript{17}. The estimation of BEER models is based on a cointegrated relationship between the exchange rate and its fundamentals. We define the cointegrated relationship - the long run equilibrium exchange rate - as follows\textsuperscript{18}:

\[ q_t = b_0 + b_1(r_t - r_t^*) + b_2(a_t - a_t^*) + b_3(niip_t - niip_t^*) + \epsilon_t \]  

(8)

With \( q_t \), the (log of the) real euro/dollar exchange rate (s dollars for 1 euro); \( (r_t - r_t^*) \), the long term real interest rate differential; \( (a_t - a_t^*) \), the productivity differential; \( (niip_t - niip_t^*) \), the differential of the ratio of the net international investment positions over GDP; \( \epsilon_t \), an error term.

The error correction model takes the following form:

\[
\Delta q_t = \sum_{i=1}^{k} \beta_{i,1}\Delta q_{t-i} + \sum_{i=-m}^{k} \beta_{i,2}\Delta(r_{t-i} - r_{t-i}^*) + \sum_{i=-m}^{k} \beta_{i,3}\Delta(a_{t-i} - a_{t-i}^*) + \sum_{i=-m}^{k} \beta_{i,4}\Delta(niip_{t-i} - niip_{t-i}^*) \\
+ \lambda \left[ q_{t-1} - b_0 - b_1(r_{t-1} - r_{t-1}^*) - b_2(a_{t-1} - a_{t-1}^*) - b_3(niip_{t-1} - niip_{t-1}^*) \right] + \epsilon_t 
\]  

(9)

In accordance with the related literature and due to data availability, the estimation of model (9) is based on a monthly frequency. The considered currencies are the euro, the pound and the yen against the dollar. Because macroeconomic adjustments happen over long periods, we consider a longer period for the tests of macroeconomic efficiency. The estimation period runs from January 1975 to December 2008\textsuperscript{19}. The method used is dynamic OLS (Banerjee \textit{et al.} (1998))\textsuperscript{20}. This method is more satisfying than relying on a VECM model given the validation of weak exogeneity for exchange rate fundamentals\textsuperscript{21}; and the willingness to build

\textsuperscript{17} We however keep in mind that BEER models have several flaws. BEER models are mainly \textit{ad hoc} models where almost any economic variable can be included (see Wadhwani (1999), Koen \textit{et al.} (2001), Camarero \textit{et al.} (2005), Bénassy-Quéré \textit{et al.} (2008)); the dynamics are based on an econometric relationship and not on an economic model; the use of an error-correction model implies that on average, over the estimation period, the exchange rate is assumed to be equal to its equilibrium value.

\textsuperscript{18} Appendix E provides a detailed description of the variables used in model (8).

\textsuperscript{19} A long time span is best-suited for the estimation of equilibrium exchange rates. Yet one limit of the approach for the euro exchange rate is that we assume that the euro area had been in place since 1975 and in particular that there was a single monetary policy since then. Prior to 1999, the euro/dollar exchange rate is calculated using the synthetic euro provided by Datastream (see appendix J).

\textsuperscript{20} We follow Banerjee \textit{et al.} (1998) by considering 4 lags \((k = 4)\) and 2 leads \((m = 2)\). Leads and lags selection is based on a recursive method: starting from the highest lag/lead, we then drop variables whose coefficients are not significant at a 5 % level.

\textsuperscript{21} See appendix F, table F.4.
a parsimonious model. We take account of the eventual presence of heteroskedasticity and autocorrelation in the residuals by applying the HAC correction of Newey-West (1987). Table 6 shows the estimation output.

<table>
<thead>
<tr>
<th>Currencies</th>
<th>$\lambda$</th>
<th>$b_0$</th>
<th>$b_1$</th>
<th>$b_2$</th>
<th>$b_3$</th>
<th>$R^2_{adj}$</th>
<th>$R^2_{adj}$</th>
<th>ARCH</th>
<th>LM</th>
<th>J&amp;B</th>
<th>RESET Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euro</td>
<td>-0.018</td>
<td>-0.500</td>
<td>0.072</td>
<td>0.138</td>
<td>0.031</td>
<td>0.10</td>
<td>0.78</td>
<td>3.11 (0.68)</td>
<td>5.13 (0.39)</td>
<td>2.48 (0.28)</td>
<td>3.25 (0.19)</td>
</tr>
<tr>
<td>Pound</td>
<td>-0.041</td>
<td>1.910</td>
<td>0.013</td>
<td>0.685</td>
<td>0.043</td>
<td>0.07</td>
<td>0.71</td>
<td>9.46 (0.00)</td>
<td>10.80 (0.05)</td>
<td>62.93 (0.00)</td>
<td>2.74 (0.25)</td>
</tr>
<tr>
<td>Yen</td>
<td>-0.038</td>
<td>-5.017</td>
<td>0.034</td>
<td>1.170</td>
<td>0.183</td>
<td>0.15</td>
<td>0.70</td>
<td>13.37 (0.02)</td>
<td>17.26 (0.00)</td>
<td>11.15 (0.00)</td>
<td>3.92 (0.14)</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; $p$-values are mentioned in brackets; critical values for the test of Student amount to 1.96 at a 5% confidence level and to 1.64 at a 10% confidence level; 5 lags are considered for ARCH and LM tests.

Diagnostic tests show that although there is some heteroskedasticity and autocorrelation in the residuals for the pound and yen models (in spite of the HAC correction), RESET tests do not reject the specification of the model used here for every currency.

Adjusted $R^2$ associated to the error correction models are rather weak (lower than 15%). This result, often found in the literature, is related to the difficulty to explain exchange rate returns based on macroeconomic fundamentals. Conversely, adjusted $R^2$ associated to the long run relationship are more satisfying since for each currency, the model explains at least 70% of the variance of the real exchange rates. The difference between the short run adjusted $R^2$ and the long run adjusted $R^2$ is related to the characteristics of the endogenous variables and the set of exogenous variables considered in the model. Equation (8) explains a financial variable - the exchange rate - by relying on a set of macroeconomic fundamentals. Macroeconomic fundamentals are low volatile variables that follow long run trends. Conversely, financial variables - exchange rates - experience higher volatility than macroeconomic fundamentals and follow short/medium run trends. This difference in the characteristics between financial variables (the endogenous variables) and macroeconomic fundamentals (the exogenous variables) explain the difference between the short run adjusted $R^2$ and the long run adjusted $R^2$.

The coefficients $\lambda$ - the speed of adjustment of the exchange rate towards its long-run value - are significant and negative. The model hence validates the existence of significant return forces that lead the exchange rate towards its equilibrium value in the long run. Moreover, all the coefficients in the long run relationship are significant and correctly signed. These results imply the acceptance of the first condition of macroeconomic efficiency.
However, return forces appear rather weak. Indeed, half-lives\textsuperscript{22} amount to almost 38 months for the euro, 17 months for the pound and 18 months for the yen.

The second condition of macroeconomic efficiency is also validated since for every currency, the coefficients related to the net external positions differentials are significant and positive. Therefore a worsening of the external position \(((niip_{t,d} - niip_{t,d}^{*}) < 0)\) induces a depreciation of the real exchange rate. This depreciation will increase the competitiveness of the economy; leading the external position towards a more sustainable path in the long run.

5.2 Testing the corollary of macroeconomic efficiency

The validation of the corollary of macroeconomic efficiency requires testing the quality of exchange rate forecasts based on fundamentals. In line with Meese and Rogoff (1983) and Cheung \textit{et al.} (2005), we analyse the performances of out-of-sample recursive forecasts\textsuperscript{23} of a BEER model compared to two alternative models. The models are defined below:

- a BEER model:
  \[
  \Delta s_{t+k}^{BEER} = \Delta q_{t+k} - \Delta p_{t+k} + \Delta p_{t+k}^{*} \tag{10}
  \]
  
  With \(\Delta q_{t+k} = b_{0,k} + b_{1,k} (r_{t} - r_{t}^{*}) + b_{2,k} (a_{t} - a_{t}^{*}) + b_{3,k} (niip_{t} - niip_{t}^{*}) + \epsilon_{t+k}\)

- a momentum rule:
  \[
  \Delta s_{t+k}^{MOM} = \mu_{k} + \nu_{k} \left[ ma_{t}^{e} - ma_{t}^{h} \right] + \epsilon_{t+k} \tag{11}
  \]
  
  With \(N_{st} = 50\) days (2 months) and \(N_{lt} = 200\) days (6 months)

- a random walk without drift:
  \[
  s_{t+k}^{RW} = s_{t} + \epsilon_{t+k} \tag{12}
  \]
  
  Where \(\epsilon_{t+k} \rightarrow iidN(0, \sigma_{\epsilon}^{2})\)

\textsuperscript{22} Half-lives, expressed in months, are computed as follows: \textit{half-life} = \(ln(0.5)/ln(1-\lambda)\).

\textsuperscript{23} Recursive forecasts aim at estimating the model in-sample for a given period of time and forecasting the endogenous variable out-of-sample. We then estimate the model by adding one observation to the previous in-sample period (the initial date of the in-sample period remains the same). We iterate this procedure until the end of the sample period.
Models are estimated in-sample from January 1975 to December 1995 based on monthly data. The out-of-sample period runs from January 1996 to December 2008. Forecast horizons span from 1 month to 10 years. Forecast errors of the different models are shown in Table 7.

Table 7: Forecast errors from a BEER model, a momentum rule (MM) and a random walk (RW)

<table>
<thead>
<tr>
<th>Currencies</th>
<th>Model</th>
<th>Stat</th>
<th>1 month</th>
<th>3 months</th>
<th>6 months</th>
<th>1 year</th>
<th>2 years</th>
<th>5 years</th>
<th>10 years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euro</td>
<td>BEER</td>
<td>RMSE</td>
<td>0.1531</td>
<td>0.1557</td>
<td>0.1604</td>
<td>0.1696</td>
<td>0.1831</td>
<td>0.1912</td>
<td>0.1140</td>
</tr>
<tr>
<td></td>
<td></td>
<td>U-Theil</td>
<td>5.08</td>
<td>2.50</td>
<td>1.88</td>
<td>1.42</td>
<td>0.98</td>
<td>0.67</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DM</td>
<td>3.01</td>
<td>2.75</td>
<td>2.31</td>
<td>1.66</td>
<td>0.04</td>
<td>-0.71</td>
<td>-1.53</td>
</tr>
<tr>
<td></td>
<td>MM</td>
<td>RMSE</td>
<td>0.0407</td>
<td>0.0593</td>
<td>0.0820</td>
<td>0.1108</td>
<td>0.1715</td>
<td>0.3193</td>
<td>0.3558</td>
</tr>
<tr>
<td></td>
<td></td>
<td>U-Theil</td>
<td>1.35</td>
<td>0.95</td>
<td>0.96</td>
<td>0.92</td>
<td>0.91</td>
<td>1.12</td>
<td>1.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DM</td>
<td>1.04</td>
<td>0.24</td>
<td>0.10</td>
<td>-0.31</td>
<td>-0.23</td>
<td>1.72</td>
<td>1.55</td>
</tr>
<tr>
<td></td>
<td>RW</td>
<td>RMSE</td>
<td>0.0301</td>
<td>0.0621</td>
<td>0.0851</td>
<td>0.1193</td>
<td>0.1865</td>
<td>0.2828</td>
<td>0.2664</td>
</tr>
<tr>
<td></td>
<td></td>
<td>U-Theil</td>
<td>0.2273</td>
<td>0.2281</td>
<td>0.2275</td>
<td>0.2330</td>
<td>0.2040</td>
<td>0.2501</td>
<td>0.1628</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DM</td>
<td>2.53</td>
<td>2.41</td>
<td>2.42</td>
<td>2.12</td>
<td>1.02</td>
<td>2.48</td>
<td>1.46</td>
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<tr>
<td></td>
<td>MM</td>
<td>RMSE</td>
<td>0.0494</td>
<td>0.0677</td>
<td>0.0958</td>
<td>0.1267</td>
<td>0.1688</td>
<td>0.3082</td>
<td>0.4160</td>
</tr>
<tr>
<td></td>
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<td>U-Theil</td>
<td>1.05</td>
<td>0.75</td>
<td>0.86</td>
<td>0.84</td>
<td>0.94</td>
<td>1.24</td>
<td>1.70</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DM</td>
<td>1.04</td>
<td>0.15</td>
<td>0.77</td>
<td>0.45</td>
<td>0.20</td>
<td>0.22</td>
<td>6.00</td>
</tr>
<tr>
<td></td>
<td>RW</td>
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<td>0.0901</td>
<td>0.1109</td>
<td>0.1494</td>
<td>0.1777</td>
<td>0.2467</td>
<td>0.2435</td>
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<tr>
<td>Pound</td>
<td>BEER</td>
<td>RMSE</td>
<td>0.1518</td>
<td>0.1572</td>
<td>0.1546</td>
<td>0.1700</td>
<td>0.1479</td>
<td>0.2061</td>
<td>0.1691</td>
</tr>
<tr>
<td></td>
<td></td>
<td>U-Theil</td>
<td>5.46</td>
<td>3.10</td>
<td>2.22</td>
<td>1.72</td>
<td>1.10</td>
<td>1.70</td>
<td>0.78</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DM</td>
<td>3.72</td>
<td>3.17</td>
<td>2.63</td>
<td>1.73</td>
<td>0.42</td>
<td>1.79</td>
<td>-0.60</td>
</tr>
<tr>
<td></td>
<td>MM</td>
<td>RMSE</td>
<td>0.0315</td>
<td>0.0469</td>
<td>0.0609</td>
<td>0.0793</td>
<td>0.1128</td>
<td>0.1428</td>
<td>0.3168</td>
</tr>
<tr>
<td></td>
<td></td>
<td>U-Theil</td>
<td>1.13</td>
<td>0.92</td>
<td>0.87</td>
<td>0.80</td>
<td>0.84</td>
<td>1.18</td>
<td>1.47</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DM</td>
<td>1.22</td>
<td>0.64</td>
<td>-0.95</td>
<td>-1.04</td>
<td>-0.91</td>
<td>1.14</td>
<td>3.00</td>
</tr>
<tr>
<td></td>
<td>RW</td>
<td>RMSE</td>
<td>0.0278</td>
<td>0.0507</td>
<td>0.0695</td>
<td>0.0985</td>
<td>0.1340</td>
<td>0.1209</td>
<td>0.2144</td>
</tr>
</tbody>
</table>

NB: RMSE = \((\sum (y_{it} - f_{it})^2)^{1/2}\); U-Theil = RMSEm/RMSEw; The Diebold and Mariano (1995) statistics (see appendix I) are computed relative to the random walk; p-values are mentioned in brackets.

At very short run horizons (1 month) and for every currency, the random walk offers the best predictions, followed by momentum rules and BEER models. For short/medium term horizons (from 3 months to 2 years), the momentum model beats the random walk and offers the best forecasts. Indeed, for every currency, U-Theils associated to the momentum rule are less than one. BEER models provide the worst predictions between 3 months and 12 months. This observation underlines the high potential of chartist rules to forecast exchange rate dynamics at short/medium run horizons. However, as long as the horizon increases, the predictive performances of chartist rules decrease significantly. Indeed, for long run horizons (between 5 years and 10 years), momentum rules provide the worst forecasts for every currency. From 5 years on, U-Theils associated to the momentum rule become higher than one.
Conversely, at long run horizons the predictive performance of BEER models is higher than the random walk. This fact is verified for the yen and the pound at 10 years as well as for the euro from 2 years on. Table 7 shows that for the majority of currencies, U-Theils associated to a BEER model decreases at 5 years and become less than one at 10 years.

As a result, in the very short run (1 month), the best forecasts are provided by the random walk; the momentum rule in the short/medium term (from 3 months to 2 years) and the BEER model for long run horizons (for 5 and 10 years). Hence, the third condition of macroeconomic efficiency is verified for every currency: in the long run, fundamentals provide the best forecasts concerning exchange rate dynamics.

5.3 Discussion of the results

Empirical results show the existence of significant return forces of exchange rates towards their fundamental value in the long run (from 2 years on). Hence exchange rates can wander away from their fundamental value in the short run, but they converge towards their fundamental value in the long run. The adjustment speed of exchange rates towards their long-run value is different across exchange rates (table 6) but strongly significant. Moreover, exchange rate models based on fundamentals (BEER models) offer better forecasts than momentum rules or random walks only in the long run (for 5 and 10 years). As a result, macroeconomic efficiency holds in the foreign exchange market in the long run, i.e. for horizons longer than 5 years. Macroeconomic efficiency does not hold for short run horizons (from 1 month to 2 years).

It follows that macroeconomic fundamentals play a major role in the determination of exchange rates especially in the long run. However, in the short run, several factors alter the relationship between exchange rates and their fundamentals. The literature often mentions nominal rigidities (Dornbush (1976)), transaction costs (De Grauwe and Grimaldi (2007)), expectations’ heterogeneity (De Grauwe and Grimaldi (2007)), etc. We argue that the disconnection of exchange rates from fundamentals in the short run could be caused by factors related to agents’ behaviours. This point is justified by surveys in the foreign exchange market. According to Cheung and Wong (2000), Cheung and Chinn (2001), Cheung et al. (2004), in the short run (from intraday frequencies to 6 months) foreign exchange market operators consider that exchange rates are exclusively driven by non-fundamental components:
speculative forces, over-reaction and bandwagon effects. Only in the long run (over 6 months) do foreign exchange market operators consider that exchange rates are determined in majority by macroeconomic fundamentals. Such results justify the empirical output obtained in table 7. In the long run, as exchange rates are mainly determined by macroeconomic fundamentals, BEER models offer the best forecasts concerning exchange rate dynamics relative to momentum rules and random walks. Conversely, in the short run, momentum rules offer the best forecasts of future exchange rates. As suggested by previous studies (Gehrig and Menkhoff (2003), Osler (2003)), chartism seems to take account of the psychological (i.e. agents’ behaviours) components affecting exchange rates. This result explains why in the short run (from 3 months to 2 years) momentum rules perform well in predicting exchange rate dynamics. On the contrary, BEER models which assume agents bereft of any psychological dimension, offer the worst forecasts at such horizon. It follows that a robust model of asset pricing should consider not solely fundamentals but also market agents’ behaviours to determine the dynamics of asset prices.

6. Different forms of efficiency for different time horizons

For every exchange rate (euro/dollar, pound/dollar and yen/dollar), results show that different forms of efficiency prevail in the foreign exchange market at different time horizons. Table 8 summarizes the results of the analysis.

---

24 See appendix H.
25 Another interpretation of the success of chartist rules to predict exchange rates at short/medium term horizons could be related to the fact that a majority of agents use chartist techniques at short/medium term horizons to forecast exchange rates.
Table 8: Results associated to the different forms of efficiency

<table>
<thead>
<tr>
<th>Type of Efficiency</th>
<th>Results</th>
<th>Conclusion</th>
</tr>
</thead>
</table>
| Fundamental Efficiency | -Rejection of UIP in the short run (from 1 month to 1 year)  
-Validation of UIP in the medium term (2 years)  
-Rejection of the REH at all horizons | Fundamental Efficiency rejected at short, medium and long run horizons |
| Macroeconomic Efficiency | -Existence of a long run relationship between exchange rates and fundamentals; significant return forces to the long run equilibrium exchange rate  
-Slow return to the equilibrium exchange rate value  
-Bad forecasting performances of BEER models in the short/medium term (from 1 month to 2 years); Better forecasting performances than random walk and momentum rules in the long run (from 5 years on) | -Rejection of macroeconomic efficiency in the short run  
-Validation of macroeconomic efficiency in the long run |
| Speculative Efficiency | -No systematic profits related to the use of chartist rules in the long run  
-Good forecasting performances of chartist rules in the medium term but not in the long run (from 5 years on) | -Rejection of speculative efficiency in the short run  
-Validation in the medium run  
-Rejection in the long run |

In the short run (between 1 month and 1 year) pure inefficiency characterises the foreign exchange market. The foreign exchange market is neither fundamentally efficient (failure of UIP between 3 months and 1 year), nor speculatively efficient (possibility to make punctual profits based on momentum or carry trade strategies; good forecasting performances of momentum rules between 3 months and 2 years), nor macroeconomically efficient (existence of long-lasting misalignments of the exchange rate from its equilibrium value in the short run and unsatisfying forecasting results with BEER models from 1 month to 2 years).

In the medium term (between 1 year and 2 years), speculative efficiency is verified in the foreign exchange market. Indeed, UIP holds for medium/long run horizons (from 2 years on) thus limiting profits related to carry trade strategies at medium/long run horizons. Profits from momentum rules or carry trades converge towards zero in the long run. Forecasts based on a momentum rule worsen at longer horizons (from 5 years on) thus limiting the profitability of such rules at long horizons. Conversely, speculative efficiency is not verified in the short run. Indeed, UIP is not validated in the short run (between 3 months and 1 year) and profits from momentum rules or carry trade strategies can be generated punctually. Also, forecasts based on a momentum rule are rather satisfying for short run horizons (between 3 months and 1 year).

In the long run (from 5 years on), the foreign exchange market is efficient from a macroeconomic perspective. Indeed, BEER models offer better forecasts between 5 years and 10 years and show the existence of significant return forces towards the long run equilibrium.
exchange rate (even if the adjustment of exchange rates towards the equilibrium value appears rather slow).

Finally, the failure of UIP in the short run (between 3 months and 1 year), the poor performances of BEER models in the short/medium term (from 1 month to 2 years) and the rejection of REH (at all horizons) lead to the rejection of fundamental efficiency - i.e. Fama’s efficiency - in the foreign exchange market whatever horizon considered.

As shown in figure 1, the foreign exchange market is characterised by different forms of efficiency for different time horizons.

Figure 1: Different forms of efficiency for different time horizons

<table>
<thead>
<tr>
<th>Pure Inefficiency</th>
<th>Speculative Efficiency</th>
<th>Macroeconomic Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short Run (1 month - 1 year)</td>
<td>Medium Run (1 year - 2 years)</td>
<td>Long Run (3 years -)</td>
</tr>
</tbody>
</table>

7. Conclusion

Starting from the internal contradictions of Fama (1965)’s definition of efficiency, the paper provides three definitions of foreign exchange market efficiency: fundamental efficiency, macroeconomic efficiency and speculative efficiency. These three distinct definitions lead to four different forms of market efficiency: fundamental efficiency, speculative efficiency, macroeconomic efficiency and pure inefficiency.

Empirical tests show that foreign exchange market efficiency is characterised by pure inefficiency in the short run (between 1 month and 1 year), speculative efficiency in the medium run (between 1 and 2 years) and macroeconomic efficiency in the long run (from 5 years on). Fundamental efficiency does not hold in the foreign exchange market. These results have important implications regarding exchange rate dynamics. The validation of macroeconomic efficiency in the long run implies that large misalignments of exchange rates can occur and persist in the short run and as such, can contribute to global imbalances.
There are several possible extensions of this work. First, the tests of foreign market efficiency can be extended to other types of exchange rates (for instance, effective exchange rates) or other bilateral exchange rates (for example, exchange rates from emerging economies). Secondly, one can improve the empirical tests associated to each form of efficiency by taking account of new econometric techniques or new data. Testing UIP and REH at higher frequencies by relying on tick-by-tick data could be an interesting way of extending this work.
References


Appendices

A. Current, forward and expected exchange rates at 3 months, 1 year and 2 years

Figures A.1 to A.6 represent the evolution of the current exchange rates, the forward exchange rates and the expected exchange rates at 3 months, 1 year and 2 years for the euro, the pound and the yen against the dollar.

Figures A.1 to A.6: Current, forward and expected exchange rates at 3 months, 1 year and 2 years

Sources: Thomson Datastream and Consensus Forecast; the euro is listed as one euro for $1$ dollars; the pound is listed as one pound for $1$ dollars and the yen is listed as one dollar for $100$ yens.
For every exchange rate, the forward exchange rate appears as a bad predictor of the future exchange rate. Besides, agents seem to make systematic errors concerning their exchange rate expectations.

For instance, in January 2000, 1 euro is equal to 1,02 dollars. The one year interest rate is equal to 5,4 % in the United States and 3,3 % in Europe. According to UIP, the market expects at one year an appreciation of 2,1 % for the euro (hence one euro for 1,04 dollars). According to Consensus Forecast, the expected value of the euro at one year is equal to 1,12 (hence an appreciation of 9,8 %). Actually, in January 2001, 1 euro is equal to 0,94 dollars (the euro has depreciated by 8,5 %).

At the beginning of 2007, 1 euro is worth 1,30 dollars. Consensus Forecast predicts 1 euro for 1,31 dollars at the beginning of 2008 (hence an appreciation of 0,8 %). Such dynamics match the interest rates differential between the US and the euro zone. Actually, in January 2008, the exchange rate is equal to 1,49 (hence an appreciation of the euro by 14,6 %).

Eventually, between January 2002 and January 2008, the dollar depreciated from 0,88 in January 2002 to 1,50 euros in January 2008. During this period, the annual returns for a US investor of a risk-free investment labelled in dollars has been on average 2,8 % a year. Conversely, over the same period, the annual returns of a risk-free investment labelled in euros amounted to 12,4 % (given the evolution of the euro/dollar exchange rate). The dollar dynamics do not match the one assumed by UIP. Had UIP held, the dollar should have had appreciated during this period. As mentioned above, the dollar has actually depreciated between January 2002 and January 2008.

The same observations can be made for the pound/dollar and the yen/dollar exchange rates.

B. Tests for uncovered interest rate parity and the rational expectations hypothesis

Fundamental efficiency assumes the validation of UIP:

\[ s_{t+k} - s_t = r_t^* - r_t \]

Empirical tests of UIP often include the forward exchange rate in the above equation. The forward rate is introduced through the covered interest rate parity (CIP). According to CIP, the spread between the forward exchange rate \( f_{t,k} \) and the actual exchange rate at time
\( t \ (s_t) \) is equal to the interest rate differential between a foreign country and a domestic country:
\[
f_{t,k} - s_t = r_t^* - r_t
\]

From the above equations, the forward rate must be equal to the future expected exchange rate:
\[
f_{t,k} = s_{t+k}^a
\]

Under REH, expectation errors made by agents \((\varepsilon_t)\) are on average equal to zero \((E[\varepsilon_t] = 0)\). In other words, agents’ expectations on the future exchange rate are on average equal to the realised values of the exchange rate in the future. Therefore, the future exchange rate is equal to the expected exchange rate plus an error term:
\[
s_{t+k} = s_{t+k}^a + \varepsilon_{t+k}
\]

Given the above equations, one can write UIP as:
\[
s_{t+k} - s_t = f_{t,k} - s_t + \varepsilon_{t+k}
\]

Under an econometric form, the above relationship becomes:
\[
s_{t+k} - s_t = \alpha + \beta(f_{t,k} - s_t) + \varepsilon_{t+k}
\]

Therefore, UIP will be verified if the following constraints are significantly accepted in the above equation: \(\alpha = 0\) and \(\beta = 1\) and \(\varepsilon_{t+k}\) follows a white noise process \((\varepsilon_{t+k} \rightarrow iidN(\mu,\sigma^2))\).
C. Tests for a time-varying risk premium

According to Frankel and Froot (1987), the omission of a time-varying risk premium can explain the failure of UIP in the short run. Indeed, equation (3) in the core text assumes risk neutral agents. The hypothesis of risk aversion implies the introduction of a time-varying risk premium ($\rho_t$) in relation (1) in the core text:

$$r_t = r_t^* - (s_{t+k} - s_t) + \varepsilon_t \quad \text{(C.1)}$$

The presence of a risk premium means that domestic and foreign assets are not perfectly substitutable anymore. Investors consider that one asset is riskier than the other one. Consequently, investors require a higher return to hold the riskier asset. Supposing that CIP holds, the risk premium can be defined as:

$$\rho_t = f_{t,k} - \Delta s_{t+k/t} \quad \text{(C.2)}$$

Based on this definition, we now define the influence of the risk premium on the coefficient $\beta$ of equation (3) in the core text and hence on the failure of UIP.

By definition, the limit probability of the coefficient $\beta$ is given by:

$$\text{plim } \beta = \frac{\text{COV}(\varepsilon_{t+k}, f_{t,k}) + \text{COV}(\Delta s_{t+k/t}, f_{t,k})}{\text{VAR}(f_{t,k})} \quad \text{(C.3)}$$

Introducing the definition of the risk premium (equation (C.2)) and readjusting, we get:

$$\beta = 1 - \frac{\text{COV}(\varepsilon_{t+k}, f_{t,k})}{\text{VAR}(f_{t,k})} - \frac{\text{VAR}(\rho_t) + \text{COV}(\Delta s_{t+k/t}, \rho_t)}{\text{VAR}(f_{t,k})} \quad \text{(C.4)}$$

Systematic errors on the future expected exchange rate

Time-varying risk premium

Hence:

$$\beta = 1 - b_{ar} - b_{pr} \quad \text{(C.5)}$$
This decomposition shows that the coefficient $\beta$ is influenced by two factors. The term $b_{ar}$ represents systematic expectation errors (or the invalidation of the REH). The term $b_{pr}$ represents the influence of a time-varying risk premium. If UIP holds, then $\beta = 1$. In this case, agents behave rationally and do not make systematic errors in their forecasts ($b_{ar} = 0$); also, the presence of a time-varying risk premium is not justified ($b_{pr} = 0$).

The failure of UIP can therefore be attributed to two factors: the presence of a time-varying risk-premium ($b_{pr} \neq 0$) and the occurrence of systematic forecasting errors by agents ($b_{ar} \neq 0$). To test whether the failure of UIP is due to a time-varying risk premium, we regress the variation in the expected exchange rate ($s^a_{t+k} - s_t$) on the forward premium ($f_{t,k} - s_t$):

$$s^a_{t+k} - s_t = \alpha + \beta(f_{t,k} - s_t) + \epsilon_{t+k} \quad (C.6)$$

The failure of UIP and hence the forward bias will be more influenced by the existence of a time-varying risk premium than systematic expectation errors if $\beta < 0.5$. In this case, the forward premium ($f_{t,k} - s_t$) is more explained by the variance of the time-varying risk-premium $\rho_t$ than by the variance of systematic expectation errors ($s^a_{t+k} - s_t$). Hence:

$$\text{VAR}(\Delta s^a_{t+k}) < \text{VAR}(\rho_t) \quad (C.7)$$

By introducing the risk premium (C.2) in (C.4) and after adjustments, we get:

$$\frac{\text{COV}(f_{t,k} \cdot \Delta s^a_{t+k})}{\text{VAR}(f_{t,k})} < 1/2 \quad (C.8)$$

From (C.3) and assuming that $\text{COV}][:t+k, f_{t,k}] = 0$, (C.8) is equal to $\beta < 0.5$. This demonstration allows testing three hypotheses from relation (C.6). First, if the constraints $\alpha = 0$ and $\beta = 1$ hold then the forward bias is explained only by systematic expectation errors and not by a time-varying risk premium. Secondly, if the constraint $\beta = 1$ is verified then a risk premium explains part of the forward bias. Thirdly, if $\beta = 0.5$ then the forward bias is equally explained by the presence of a time-varying risk premium and by systematic expectation errors.
D. Stationarity tests for UIP tests (table 1 in the core text), time-varying risk premium tests (table 2 in the core text) and REH tests (table 3 in the core text)

Stationarity tests are based on three tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Results are presented in tables D.1, D.2 and D.3.

Table D.1: Stationarity tests for the endogenous variable \((s_{t+k} - s_t)\) for UIP and REH tests

<table>
<thead>
<tr>
<th>(s_{t+k} - s_t)</th>
<th>(k = 3)</th>
<th>(k = 12)</th>
<th>(k = 24)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tests</strong></td>
<td><strong>ADF</strong></td>
<td><strong>PP</strong></td>
<td><strong>KPSS</strong></td>
</tr>
<tr>
<td>Euro</td>
<td>-3.24*</td>
<td>-2.91</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.16)</td>
<td></td>
</tr>
<tr>
<td>Pound</td>
<td>-0.73</td>
<td>-3.23**</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>(0.96)</td>
<td>(0.08)</td>
<td></td>
</tr>
<tr>
<td>Yen</td>
<td>-1.86</td>
<td>-4.43***</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.66)</td>
<td>(0.00)</td>
<td></td>
</tr>
</tbody>
</table>

NB: *p-values* are mentioned in brackets; one star (*), two stars (**) and three stars (***) denote respectively a stationary series at a 10 %, 5 % and 1% confidence level.

Table D.2: Stationarity tests for the exogenous variables \((f_{t,k} - s_t)\) in UIP tests

<table>
<thead>
<tr>
<th>(f_{t,k} - s_t)</th>
<th><strong>ADF</strong></th>
<th><strong>PP</strong></th>
<th><strong>KPSS</strong></th>
<th><strong>ADF</strong></th>
<th><strong>PP</strong></th>
<th><strong>KPSS</strong></th>
<th><strong>ADF</strong></th>
<th><strong>PP</strong></th>
<th><strong>KPSS</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tests</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Euro</td>
<td>-4.03**</td>
<td>-1.59</td>
<td>0.18</td>
<td>-1.67</td>
<td>-1.81</td>
<td>0.17</td>
<td>-2.03</td>
<td>-2.16</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.78)</td>
<td></td>
<td>(0.75)</td>
<td>(0.68)</td>
<td></td>
<td>(0.56)</td>
<td>(0.50)</td>
<td></td>
</tr>
<tr>
<td>Pound</td>
<td>-3.87**</td>
<td>-8.71***</td>
<td>0.13</td>
<td>-1.56</td>
<td>-1.70</td>
<td>0.17</td>
<td>-1.96</td>
<td>-2.02</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.00)</td>
<td></td>
<td>(0.80)</td>
<td>(0.74)</td>
<td></td>
<td>(0.60)</td>
<td>(0.57)</td>
<td></td>
</tr>
<tr>
<td>Yen</td>
<td>-2.44</td>
<td>-6.04***</td>
<td>0.16</td>
<td>-1.43</td>
<td>-1.43</td>
<td>0.20</td>
<td>-2.25</td>
<td>-2.25</td>
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</tr>
<tr>
<td></td>
<td>(0.35)</td>
<td>(0.00)</td>
<td></td>
<td>(0.84)</td>
<td>(0.84)</td>
<td></td>
<td>(0.45)</td>
<td>(0.45)</td>
<td></td>
</tr>
</tbody>
</table>

NB: *p-values* are mentioned in brackets; one star (*), two stars (**) and three stars (***) denote respectively a stationary series at a 10 %, 5 % and 1% confidence level.

Table D.3: Stationarity tests for the exogenous variables \((s'_{t+k} - s_t)\) in REH tests

<table>
<thead>
<tr>
<th>(s'_{t+k} - s_t)</th>
<th><strong>ADF</strong></th>
<th><strong>PP</strong></th>
<th><strong>KPSS</strong></th>
<th><strong>ADF</strong></th>
<th><strong>PP</strong></th>
<th><strong>KPSS</strong></th>
<th><strong>ADF</strong></th>
<th><strong>PP</strong></th>
<th><strong>KPSS</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tests</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Euro</td>
<td>-4.19***</td>
<td>-5.94***</td>
<td>0.08</td>
<td>-3.83**</td>
<td>-3.82**</td>
<td>0.08</td>
<td>-3.21*</td>
<td>-3.25*</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
<td>(0.08)</td>
<td>(0.07)</td>
<td></td>
</tr>
<tr>
<td>Pound</td>
<td>-3.87*</td>
<td>-8.71***</td>
<td>0.13</td>
<td>-3.38*</td>
<td>-4.81***</td>
<td>0.12</td>
<td>-3.46**</td>
<td>-3.34*</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.00)</td>
<td></td>
<td>(0.05)</td>
<td>(0.00)</td>
<td></td>
<td>(0.04)</td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td>Yen</td>
<td>-2.44</td>
<td>-6.04***</td>
<td>0.16</td>
<td>-1.58</td>
<td>-2.73</td>
<td>0.13</td>
<td>-1.47</td>
<td>-2.31</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
<td>(0.00)</td>
<td></td>
<td>(0.79)</td>
<td>(0.22)</td>
<td></td>
<td>(0.83)</td>
<td>(0.42)</td>
<td></td>
</tr>
</tbody>
</table>

NB: *p-values* are mentioned in brackets; one star (*), two stars (**) and three stars (***) denote respectively a stationary series at a 10 %, 5 % and 1% confidence level.

Results concerning stationarity tests are mixed. A given series can be stationary or not stationary depending on the chosen test. As in the sample period (January 1999-December 2008), the considered exchange rates are highly volatile in level, we consider exchange rate series are integrated of order one.
Table D.4 presents the cointegration tests of equations (3), (4) and (5) in the core text.

Table D.4: Cointegration tests associated to equation (3), equation (4) and equation (5)

<table>
<thead>
<tr>
<th>Currencies</th>
<th>Horizon</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><strong>UIP</strong> (equation (3))</td>
</tr>
<tr>
<td>Euro</td>
<td>3</td>
<td>Trace 2 MaxEig 1</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>Trace 0 MaxEig 1</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>Trace 0 MaxEig 1</td>
</tr>
<tr>
<td>Pound</td>
<td>3</td>
<td>Trace 2 MaxEig 1</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>Trace 0 MaxEig 1</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>Trace 1 MaxEig 1</td>
</tr>
<tr>
<td>Yen</td>
<td>3</td>
<td>Trace 1 MaxEig 1</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>Trace 0 MaxEig 1</td>
</tr>
<tr>
<td></td>
<td>24</td>
<td>Trace 0 MaxEig 1</td>
</tr>
</tbody>
</table>

NB: Cointegration tests are based on the following assumptions: Data Trend: Linear; Test Type: Intercept, No Trend; UIP stands for the test for uncovered interest rate parity *ex post*; TVRA stands for the tests for a time-varying risk aversion; REH stands for the test for the rational expectations hypothesis; Critical values are based on the table of MacKinnon-Haug-Michelis (1999).

Cointegration tests show the existence of a significant cointegrated relationship between the endogenous and the exogenous variables considered in equations (3), (4) and (5) for all currencies except for the yen in equations (4) and (5) respectively at 1 and 2 years.

E. Description of the variables used in the BEER model

E.1 Endogenous variable: the real exchange rate

\[ q_t = \log(Q_t) = \log(S_t/P_t) \]

With \( S_t \), the euro/dollar exchange rate (1 euro for \( S \) dollars); \( P_t \), the consumer price index in the United States; \( P_t \), the consumer price index in the Euro zone.
E.2 Exogenous variables

- **Long term interest rate differential:**

\[(r_t - r_t^*) = (i_t - \pi_t) - (i_t^* - \pi_t^*)\]

With \(\pi_t = \frac{CPI_t - CPI_{t-12}}{CPI_{t-12}} \times 100\) and \(\pi_t^* = \frac{CPI_t^* - CPI_{t-12}^*}{CPI_{t-12}^*} \times 100\); \(i_t\) and \(i_t^*\), respectively the nominal interest rates on 10-years bonds for the Euro zone and the United States; \(\pi_t\) and \(\pi_t^*\), the inflation rates in the Euro zone and in the United States computed as the growth rate of the consumer price index in the Euro zone \((CPI_t)\) and in the United States \((CPI_t^*)\).

- **Productivity differential:**

\[(a_t - a_t^*) = \log(GDP_t/L_t) - \log(GDP_t^*/L_t^*)\]

With \(GDP_t\) and \(GDP_t^*\), the gross domestic products in the Euro zone and in the United States; \(L_t\) and \(L_t^*\), the number of employed people in the Euro zone and in the United States.

- **Net international investment position differential:**

\[(niip_t - niip_t^*) = NIIP_t/GDP_t - NIIP_t^*/GDP_t^*\]

With \(NIIP_t\) and \(NIIP_t^*\) respectively, the net international investment position of the Euro zone and the United States; \(GDP_t\) and \(GDP_t^*\), the gross domestic product in the Euro zone and in the United States. The series \((niip_t - niip_t^*)\) have been filtered with a Hodrick-Prescott filter. This filter is often used in the literature to smooth series available at lower frequencies. Indeed, the BEER model is estimated on a monthly frequency while data on net international investment positions are only available annually. Besides, without filtering, we get an incorrect sign for this variable in equation (8) in the core text.
F. Test procedure for the BEER model

The estimation procedure of the BEER model follows three steps. The first step verifies whether all series have the same order of integration. Table F.1 shows that all series are integrated of order one.

Table F.1: Integration order for the series used in the BEER models for the euro, the pound and the yen

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_t$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>$(r_t - r^*_t)$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>$(a_t - a^*_t)$</td>
<td>I(1)</td>
<td>I(2)</td>
<td>I(1)</td>
</tr>
<tr>
<td>$(niip_t - niip^*_t)$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
</tbody>
</table>

In a second step, we look for the number of cointegrated vectors by applying Trace tests and Maximum Eigenvalue tests. Results available in table F.2 (column 4) validate the presence of at most one cointegrated vector between the exchange rate and its fundamentals. We therefore estimate a univariate error correction model.

Table F.2: Number of cointegrated vectors at a 5% confidence level

<table>
<thead>
<tr>
<th></th>
<th>Euro</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>None</td>
<td>None</td>
<td>Linear</td>
<td>Linear</td>
<td>Quadratic</td>
</tr>
<tr>
<td>Type de Test</td>
<td>No Intercept</td>
<td>No Trend</td>
<td>Intercept</td>
<td>No Trend</td>
<td>Intercept</td>
<td>Trend</td>
</tr>
<tr>
<td>Trace</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Max-Eigenvalue</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>None</th>
<th>None</th>
<th>Linear</th>
<th>Linear</th>
<th>Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type de Test</td>
<td>No Intercept</td>
<td>No Trend</td>
<td>Intercept</td>
<td>No Trend</td>
<td>Intercept</td>
<td>Trend</td>
</tr>
<tr>
<td>Trace</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Max-Eigenvalue</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th>None</th>
<th>None</th>
<th>Linear</th>
<th>Linear</th>
<th>Quadratic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type de Test</td>
<td>No Intercept</td>
<td>No Trend</td>
<td>Intercept</td>
<td>No Trend</td>
<td>Intercept</td>
<td>Trend</td>
</tr>
<tr>
<td>Trace</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Max-Eigenvalue</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

NB: Critical values are based on the tables of MacKinnon, Haug and Michelis (1999).

In a third step, we estimate the long run relationship (equation (8) in the core text) by ordinary least squares (OLS). We then test for stationary residuals in equation (8). Table F.3 shows that residuals in the long run relationships are stationary. We therefore estimate the error correction model. Results are available in table 6 in the core text.
To justify the estimation of a univariate ECM, we compute weak exogeneity tests on the following VECM:

\[
\Delta X_t = \sum_{i=1}^{p} \Gamma_i \Delta X_{t,i} + \Pi Z_{t-1} + \epsilon_t
\]

Where \( X \) is a \((nx1)\) vector, with \( n \) representing the number of variables considered in the model; \( \Gamma_i \) is a \((nxn)\) matrix; \( \Pi \) is a \((nxn)\) matrix, whose rank determines the number of cointegrated vectors; \( \epsilon_t \) is a \((nx1)\) error term vector assumed to follow a white noise process.

The matrix \( \Pi \) can be split into two vectors \( a \) and \( b \) such that:

\[
\Pi = ab^\prime
\]

Where \( a \) is a \((nxr)\) matrix that contains the adjustment parameters towards the long run relationship \( (r \) represents the number of cointegrated relationships); \( b \) is a \((nxr)\) matrix that defines the coefficients in the long-run relationship.
Assuming the existence of a unique long-run relationship \((r = 1)\), we have:

\[
\Delta q_t = \lambda_1 [E_{t-1}] + \sum_{i=1}^{p} \delta_{i1} \Delta q_t + \sum_{i=1}^{p} \mu_{i1} \Delta (r_t - r_t^*) + \sum_{i=1}^{p} \gamma_{i1} \Delta (a_t - a_t^*) + \sum_{i=1}^{p} \eta_{i1} \Delta (niip_t - niip_t^*) + \varepsilon_{1,t}
\]

\[
\Delta (r_t - r_t^*) = \lambda_2 [E_{t-1}] + \sum_{i=1}^{p} \delta_{i2} \Delta q_t + \sum_{i=1}^{p} \mu_{i2} \Delta (r_t - r_t^*) + \sum_{i=1}^{p} \gamma_{i2} \Delta (a_t - a_t^*) + \sum_{i=1}^{p} \eta_{i2} \Delta (niip_t - niip_t^*) + \varepsilon_{2,t}
\]

\[
\Delta (a_t - a_t^*) = \lambda_3 [E_{t-1}] + \sum_{i=1}^{p} \delta_{i3} \Delta q_t + \sum_{i=1}^{p} \mu_{i3} \Delta (r_t - r_t^*) + \sum_{i=1}^{p} \gamma_{i3} \Delta (a_t - a_t^*) + \sum_{i=1}^{p} \eta_{i3} \Delta (niip_t - niip_t^*) + \varepsilon_{3,t}
\]

\[
\Delta (niip_t - niip_t^*) = \lambda_4 [E_{t-1}] + \sum_{i=1}^{p} \delta_{i4} \Delta q_t + \sum_{i=1}^{p} \mu_{i4} \Delta (r_t - r_t^*) + \sum_{i=1}^{p} \gamma_{i4} \Delta (a_t - a_t^*) + \sum_{i=1}^{p} \eta_{i4} \Delta (niip_t - niip_t^*) + \varepsilon_{4,t}
\]

With \( \Pi = ab' \) where \( a = \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{pmatrix} \) and \( b' = (1 \beta_0 \beta_1 \beta_2 \beta_3) \)

And \( E_{t-1} = q_{t-1} - \beta_0 - \beta_1 (r_{t-1} - r_{t-1}^*) - \beta_2 (a_{t-1} - a_{t-1}^*) - \beta_3 (niip_{t-1} - niip_{t-1}^*) \)

The normalisation suggests that \( q_t \) is endogenous and \((r_t - r_t^*), (a_t - a_t^*), (niip_t - niip_t^*)\) are weakly exogenous for the parameters in the vectors \( a \) and \( b \). Thus, the test of a parameter equal to zero in the rows of vector \( a \) is equivalent to testing whether a variable can be considered as weakly exogenous in the long-run parameters of the vector \( b \) (Johansen (1995), Juselius (2006)). For example \( q_t \) is weakly exogenous for the vector \( b \) (long run weakly exogenous) if \( \lambda_1 \) is significantly equal to zero \((\lambda_1 = 0)\). In the same vein, if \( (r_t - r_t^*) \) is weakly exogenous then \( \lambda_2 = 0 \). If the zero restriction is significant then the variable \((r_t - r_t^*)\) is weakly exogenous. In other words, the variable \((r_t - r_t^*)\) does not respond to any deviation from the long-run equilibrium.

Tests for weak exogeneity are based on a Likelihood Ratio statistic:

\[
LR = -2[\ln(L_C) - \ln(L_{NC})] \sim \chi^2(v)
\]

Where \( v \) is the number of constraints; \( L_C \), the likelihood of the constrained model; \( L_{NC} \), the likelihood of the unconstrained model. If the \( LR \) statistics is higher than the \( \chi^2(v) \) at a confidence level \( \alpha \) then \( H_0 \) is rejected and the restrictions are not significant.
Table F.4: Results for weak exogeneity tests

<table>
<thead>
<tr>
<th>Currencies</th>
<th>( q_t )</th>
<th>((r_t - r_t^*))</th>
<th>((a_t - a_t^*))</th>
<th>((niip_t - niip_t^*))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euro</td>
<td>5,11</td>
<td>2,71 (0,09)</td>
<td>3,43 (0,06)</td>
<td>0,12 (0,72)</td>
</tr>
<tr>
<td>Pound</td>
<td>7,80</td>
<td>2,97 (0,08)</td>
<td>0,56 (0,45)</td>
<td>2,19 (0,13)</td>
</tr>
<tr>
<td>Yen</td>
<td>6,00</td>
<td>0,65 (0,41)</td>
<td>4,07 (0,05)</td>
<td>0,27 (0,60)</td>
</tr>
</tbody>
</table>

NB: LR test follows a \( \chi^2(v) \); \( p \)-values are mentioned in brackets.

The variable \( q_t \) is not considered as weakly exogenous at a 5 % confidence level. Conversely, the variables \((r_t - r_t^*), (a_t - a_t^*), (niip_t - niip_t^*)\) can be considered as weakly exogenous at a 5 % confidence level. Weak exogeneity tests thus justify the estimation of a univariate ECM model rather than a multivariate ECM model.

G. Fundamental and actual exchange rates

Figures G.1 to G.3 represent the dynamics of the observed exchange rate and the estimated fundamental exchange rate based on a BEER model for the euro, the pound and the yen against the dollar.

**Figure G.1: Euro/dollar fundamental and actual exchange rates**

![Graph showing the dynamics of the Euro/dollar fundamental and actual exchange rates. The black line represents the actual exchange rate (left scale); the grey line represents the estimated fundamental exchange rate (left scale); the green (red) area represents periods of overvaluation (undervaluation) (right scale).](image)

NB: The black line represents the actual exchange rate (left scale); the grey line represents the estimated fundamental exchange rate (left scale); the green (red) area represents periods of overvaluation (undervaluation) (right scale).

The euro is undervalued relative to the dollar in the 1980s and following its introduction between 1999 and 2003. The former observation is due to the strong appreciation of the dollar in the 1980s while the later one can be attributed to fears among market participants concerning the introduction of a new currency and a new central bank (the
European Central Bank). The euro seems overvalued against the dollar from 2003 until the end of the sample period.

**Figure G.2: Pound/dollar fundamental and actual exchange rates**

![Graph showing the exchange rates of pound/dollar]

NB: The black line represents the actual exchange rate (left scale); the grey line represents the estimated fundamental exchange rate (left scale); the green (red) area represents periods of overvaluation (undervaluation) (right scale).

Periods of overvaluation and undervaluation of the pound are close to the ones identified for the euro. The pound is undervalued relative to the dollar during the first half of the 1980s and in the 1990s. Periods of overvaluation for the pound are located in the late 1980s and at the end of the sample period.

**Figure G.3: Yen/dollar fundamental and actual exchange rates**

![Graph showing the exchange rates of yen/dollar]

NB: The black line represents the actual exchange rate (left scale); the grey line represents the estimated fundamental exchange rate (left scale); the green (red) area represents periods of overvaluation (undervaluation) (right scale); the estimation period begins in January 1985 for the yen since the Japanese external debt is only available from January 1985.
The yen is overvalued at the times of the Japanese economic boom in the late 1980s. However, after the burst of the Japanese stock price bubble and house price bubble in the early 1990s, the overvaluation of the yen progressively disappears. The yen enters in a phase of undervaluation. This phase is concomitant with the deep recession of the Japanese economy in the 1990s until the end of the sample period.

H. Factors determining exchange rates according to surveys among market practitioners

Tables H.1 to H.3 report the results of three surveys led on three major foreign exchange market places. Market practitioners were asked to provide the main determinants of exchange rates according to time horizon.

Table H.1: Factors determining exchange rate movements in Tokyo, Hong-Kong and Singapore foreign exchange market (Cheung and Wong (2000))

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>24,40</td>
<td>12,13</td>
<td>0,84</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>30,16</td>
<td>1,98</td>
<td>0,20</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>30,82</td>
<td>14,0</td>
<td>2,30</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0,70</td>
<td>32,14</td>
<td>79,56</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>13,92</td>
<td>39,75</td>
<td>17,1</td>
</tr>
</tbody>
</table>

Source: Cheung and Wong (2000); Percentages of respondents in each category are mentioned.

Table H.2: Factors determining exchange rate movements in the US foreign exchange rate market (Cheung and Chinn (2001))

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>28,20</td>
<td>10,52</td>
<td>3,93</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>30,45</td>
<td>2,10</td>
<td>0</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>25,51</td>
<td>23,68</td>
<td>2,36</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0,82</td>
<td>32,10</td>
<td>87,40</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>14,40</td>
<td>30,52</td>
<td>3,14</td>
</tr>
<tr>
<td>Other</td>
<td>0,62</td>
<td>1,08</td>
<td>3,17</td>
</tr>
</tbody>
</table>

Source: Cheung and Chinn (2001); Percentages of respondents in each category are mentioned.

Table H.3: Factors affecting exchange rate dynamics in the UK foreign exchange rate market (Cheung, Chinn and Marsh (2004))

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>29,3</td>
<td>9,5</td>
<td>1</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>32,8</td>
<td>0,7</td>
<td>0</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>25,3</td>
<td>30,7</td>
<td>3,1</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0,6</td>
<td>31,4</td>
<td>82,5</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>10,3</td>
<td>26,3</td>
<td>11,3</td>
</tr>
<tr>
<td>Other</td>
<td>1,7</td>
<td>1,5</td>
<td>2,1</td>
</tr>
</tbody>
</table>

Source: Cheung, Chinn and Marsh (2004); Percentages of respondents in each category are mentioned.
All three surveys reach the same conclusions. In the short run (intraday to horizons shorter than 6 months), market psychology (bandwagon effects, over-reaction to news and speculative forces) dominates in the determination of the exchange rate while in the long run (for horizons longer than 6 months), macroeconomic fundamentals dominate in the determination of exchange rate dynamics.

I. The Diebold and Mariano (1995) test statistic

The Diebold and Mariano (1995) test statistic is defined as follows:

\[ DM = \frac{\bar{d}}{\sqrt{\frac{2\pi \hat{f}_d(0)}{N_f}}} \]

With \( \bar{d} \), the mean of the difference series between the forecast errors of a given model \( M \) at time \( k \) (\( e^M_k \)) and the forecast errors of the random walk model (\( RW \)) without drift at time \( k \) (\( e^{RW}_k \)):

\[ \bar{d} = \frac{1}{N} \sum_{k=1}^{N} \left[ (e^M_k)^2 - (e^{RW}_k)^2 \right] \]

\( \hat{f}_d(0) \) is the spectral density in zero of \( (e^M_k)^2 - (e^{RW}_k)^2 \) estimated by the non-parametric approximation of Newey-West (1987). Under the null hypothesis, the mean of the difference series of the squared errors is null (\( \bar{d} = 0 \)). The \( DM \) statistic follows asymptotically a standard normal distribution.
J. Definition of the synthetic euro/dollar exchange rate

In this study, we rely on the synthetic euro/dollar exchange rate delivered by Datastream. The Datastream mnemonic code for the series is USEURSN. Details of how Datastream computes the synthetic euro/dollar exchange rate are provided below. The formula of the synthetic euro/dollar exchange rate is based on:

1. The US Dollar/Euro irrevocable fixed conversion rate of 1 euro per 1 dollar;
2. The cross rates to the US Dollar as published on May 4th 1998;
3. The weighting factor is constant and is the 1996 GDP weight of each country in the total GDP of the euro zone;

\[
\text{USEURSN} = (\alpha_1 S_1 \times \text{DMARKER/AUSTSCH} + \alpha_2 S_2 \times \text{DMARKER/BELGLUX} \\
+ \alpha_3 S_3 \times \text{DMARKER/FINMARK} + \alpha_4 S_4 \times \text{DMARKER/FRENFRA} \\
+ \alpha_5 S_5 \times \text{DMARKER/IPUNDER} + \alpha_6 S_6 \times \text{DMARKER/ITALIRE} \\
+ \alpha_7 S_7 \times \text{DMARKER/GUILDER} + \alpha_8 S_8 \times \text{DMARKER/PORTESC} \\
+ \alpha_9 S_9 \times \text{DMARKER/SPANPES} + 0.31315) \times 1
\]

\[
\text{USEURSN} = (0.03139 \times S_1 \times \text{DMARKER/AUSTSCH} + 0.03866 \times S_2 \times \text{DMARKER/BELGLUX} \\
+ 0.02339 \times S_3 \times \text{DMARKER/FINMARK} + 0.22064 \times S_4 \times \text{DMARKER/FRENFRA} \\
+ 0.01132 \times S_5 \times \text{DMARKER/IPUNDER} + 0.20039 \times S_6 \times \text{DMARKER/ITALIRE} \\
+ 0.05596 \times S_7 \times \text{DMARKER/GUILDER} + 0.01255 \times S_8 \times \text{DMARKER/PORTESC} \\
+ 0.09257 \times S_9 \times \text{DMARKER/SPANPES} + 0.31315) \times 1
\]

With, \( \alpha_i \), the 1996 GDP weights of the respective members of the euro zone (e.g. 0,03139 (3.139 %) is the weight of Austria; 0,22064 (22.064 %) is the weight of France; 0,31315 (31,315 %) is the weight of Germany); \( S_i \), the fixed exchange rate of each euro members to 1 US Dollar as published in May 4th 1998 (e.g. \( S_1 \) stands for the Austrian schillings and \( S_2 \) stands for the French francs).
Article 2

Inside the Black Box: Why are Order Flows Models of Exchange Rate more competitive than Traditional Models of Exchange Rate?

Abstract

This article looks inside the black box of order flows to understand why order flows models of exchange rate are more competitive than traditional models of exchange rate. We set a theoretical model that relies on a behavioural exchange rate model and a microstructure model. The model puts forward three results. First, simulations replicate stylised facts observed in the foreign exchange market. Secondly, the model shows that the foreign exchange market is intrinsically inefficient. Incoming information is distorted by behavioural noise and microstructure noise. Thirdly, order flows models of exchange rate provide an answer to the exchange rate disconnection puzzle. Indeed, order flows contain processed information \textit{i.e.} a time-varying weight of fundamental information, behavioural information and microstructure information while traditional models only consider raw information \textit{i.e.} fundamental information.

\textbf{Keywords:} Behavioural Finance, Microstructure, Order Flows Models, Market Efficiency, Exchange Rate Disconnection Puzzle
Résumé

Cet article analyse la boîte noire des modèles à flux d’ordre pour comprendre le succès des flux d’ordre dans l’explication et la prévision des taux de change relativement aux modèles traditionnels de change. Nous construisons un modèle théorique qui se compose d’un modèle à agents hétérogènes et d’un modèle de microstructure du marché des changes. Trois résultats sont mis en avant. Premièrement, les simulations répliquent d’importants faits stylisés observés sur le marché des changes. Deuxièmement, le modèle montre que le marché des changes est intrinsèquement inefficace. En effet, l’information est altérée tant par le bruit issu des comportements des agents que par le bruit inhérent à la microstructure du marché des changes. Troisièmement, les modèles à flux d’ordre fournissent une réponse à l’énigme de la déconnexion des taux de change car les flux d’ordre contiennent de l’information déjà traitée par les agents tandis que les modèles traditionnels considèrent uniquement de l’information brute i.e. non traitée.

Mots-Clés: Finance Comportementale, Microstructure, Modèles à Flux d’Ordre, Efficience des Marchés, Enigme de la Déconnexion des Taux de Change
1. Introduction

Following decades of empirical failure to explain and forecast exchange rates dynamics based on traditional exchange rate models (Meese and Rogoff, 1983), Cheung et al. (2005)), the recent microstructure literature offers promising results. Microstructure models based on order flows provide better explanatory and predictive powers in forecasting exchange rate dynamics than traditional models; especially at short horizons (Evans and Lyons (2002a, 2002b), Danielsson et al. (2002), Berger et al. (2008), Chinn and Moore (2008)). To justify this performance, order flows theorists claim that order flow includes private information about exchange rate fundamentals (Lyons (2001), Evans and Lyons (2008), Chinn and Moore (2008), Rime et al. (2010)). However, many studies counter this view. Such studies show that order flows only convey information about liquidity effects, temporary preferences and other demand shocks. Both views raise a debate between respectively the proponents of the strong flow centric view and the ones of the weak flow centric view.

This paper defends the idea that order flows contain information from both the strong and the weak flow centric views; but not solely. The article investigates inside the black box of order flows to unveil the various types of information contained in order flows. This question is becoming increasingly important as the black box has been shifted from understanding exchange rate determination to understanding order flow determination. We set a theoretical model of the foreign exchange market that describes how the initial information arriving to market agents is embedded into the final price of the currency.

The most related studies to this paper are Bachetta and van Wincoop (2006) and Evans (2010). Bachetta and van Wincoop (2006) provide an analytical framework which regroups both the strong and the weak flow centric views. Their main finding is that information heterogeneity disconnects the exchange rate from observed macroeconomic fundamentals in the short run, while there is a close relationship in the long run. At the same time, there is a close link between exchange rate dynamics and order flows over all horizons. Evans (2010) presents a theoretical model to analyse the links between high frequency spot exchange rates, order flows and macroeconomic developments. Evans finds that trades between dealers and customers convey information to dealers about the current state of the economy which dealers then use to revise their spot exchange rate quotes.

The model presented here departs from Bachetta and van Wincoop (2006) and Evans (2010) in several ways. Indeed, both models miss a major component of exchange rate
determination in the short run: agents’ behaviours (Cheung and Wong (2000), Cheung and Chinn (2001), Cheung, Chinn and Marsh (2004)). Our modelling approach integrates not solely the public and private information as in Bachetta and van Wincoop (2006) and Evans (2010) but also behavioural components affecting customers and dealers’ decisions. Our model therefore merges two strands of the literature: behavioural exchange rate models and microstructure models of exchange rate. The model puts forward three results. First, simulations replicate important stylised facts observed in the foreign exchange market. In the short run, the exchange rate is disconnected from its fundamental value but not from order flows. In the long run, the exchange rate returns towards its fundamental value and remains close to order flows. Customer and interdealer order flows are highly correlated with exchange rate dynamics at all horizons. Besides the hot potato effect magnifies the amount of interdealer order flows relative to the amount of customer order flows. Secondly, the model indicates that the foreign exchange market is intrinsically inefficient. The introduction of incoming information in the final price of the currency is distorted by agents’ behaviours (behavioural noise) and by the trading mechanism peculiar to the foreign exchange market (microstructure noise). Thirdly, the model explains why order flows provide an answer to the exchange rate disconnection puzzle. Order flows contain information processed by agents while traditional models only consider raw information. Processed information includes a time-varying weight of fundamental information (both public and private), behavioural information (both public and private) and microstructure information. Conversely, information considered in traditional models only includes public fundamental information. The difference in the types of information considered by order flows models and traditional models explains why order flows models provide higher explanatory and predictive powers of exchange rate dynamics relative to traditional models.

The remainder of the paper comprises 5 sections. Section 2 provides evidence of the high explanatory and predictive powers of order flows models. Section 3 proposes a literature survey concerning the information contained in order flows. Section 4 presents a theoretical model of the foreign exchange market and exposes the simulations provided by the theoretical model. Section 5 addresses the question of foreign exchange market efficiency and explains why order flows models come as a resolution to the exchange rate disconnection puzzle. Section 6 concludes.
2. On the competitive performances of order flows models of exchange rate

In a pioneered work, Evans and Lyons (2001, 2002) came up with an hybrid model based on private and public information to explain exchange rate dynamics. The hybrid model takes the following form:

\[
\Delta s_t = \beta_0 + \beta_1 \Delta (i_t - i_t^*) + \beta_2 \Delta X_t + \epsilon_t \tag{1}
\]

With \(s_t\), the (log of the) spot exchange rate (an increase in \(s\) is equal to an appreciation of the domestic currency); \((i_t - i_t^*)\), the interest rate differential between the domestic country and the foreign country; \(X_t\), the net cumulated order flow. \(\Delta\) stands for the first difference of the series.

Macroeconomic fundamentals (here the interest rate differential \((i_t - i_t^*)\)) represent public information known by all agents. Order flows \(X_t\) represent private information known by a minority of agents. Order flow is defined as the net of buyer- and seller-initiated currency transactions. Intuitively, order flow represents a willingness to back one's beliefs on future exchange rate dynamics, with real money.

Evans and Lyons tested their model on the deutschmark/dollar, yen/dollar and pound/dollar in daily frequency from May 1996 to August 1996. They show that private information (order flows) explain at best 65 % of the variance of exchange rates. On the contrary, public information (the interest rate differential) only explains at best 5 % of the variance of exchange rates (a figure close to the ones obtained with traditional exchange rate models). Similar results can be found in the literature as shown in table 1.
Table 1: Literature survey of the in-sample performances of order flows models

<table>
<thead>
<tr>
<th>Authors</th>
<th>Period</th>
<th>Frequency</th>
<th>Exogenous variable</th>
<th>Endogenous variable</th>
<th>Explanatory Power (R²)</th>
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<td>Yen/Dollar</td>
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<td>Yen/Dollar</td>
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<td>Yen/Dollar</td>
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<td>Pound/Dollar</td>
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<td>Euro/Pound</td>
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<td>Yen/Dollar</td>
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NB: The regression method used in the studies mentioned in table 1 is ordinary least squares (OLS)

Table 1 shows that the explanatory power of order flows models far exceeds the one of traditional models of exchange rate. For daily and weekly frequencies, the coefficients of determination (R²) spread between 30 % and 67 % (except for Danielsson et al. (2002)). At such frequencies, traditional exchange rate models usually provide R² close to or less than 10 %. Beyond the explanatory performance of exchange rates, order flows provide also better exchange rate forecasts than traditional models. A lot of studies show that order flows models beat the random walk in the short run (Evans and Lyons (2001, 2002a, 2002b, 2005a, 2006), Lindahl and Rime (2006), Rime et al. (2010)).

The results from order flows models have to be put into perspective. The relationship between order flows and exchange rate dynamics is strong at intradaily, daily and weekly frequencies but becomes weaker at lower frequencies. For example, table 1 shows that in Berger et al. (2008), order flows explain about 50 % of the variance of exchange rates at daily

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26 A detailed description of order flows is available in appendix A.
and weekly frequencies. At lower frequencies, for instance monthly frequencies, the $R^2$ declines gradually and falls to 34% for the yen/dollar exchange rate and to 21% for the euro/dollar exchange rate. The same observation stands in Chinn and Moore (2008). Therefore the explanatory power of exchange rate variation by order flows models falls at monthly frequencies. In some cases, the explanatory power comes even close to the one offered by traditional exchange rate models (see Chinn and Moore (2008)) while in other cases the explanatory power is still higher than the explanatory power of traditional exchange rate models based on fundamentals (see Berger et al. (2008))\(^\text{27}\). Still, despite the relative fall in the explanatory power of order flows models at monthly frequencies, the literature review in table 1 provides evidence of the high explanatory and predictive performances of order flows models at short run horizons (from intradaily to weekly frequencies). As a result, one may wonder which types of information do order flows contain to justify such a high explanatory power of exchange rates at short horizons?

3. The informational content of order flows: a literature review

According to Lyons (2001), order flow contains private information. Private information can be split into three components: fundamental information, liquidity effects and portfolio balance effects.

Fundamental information includes private information about exchange rate fundamentals. For example, if a central bank intervenes in the foreign exchange market by transmitting a positive order flow to a market-maker, then this market-maker will infer a likely appreciation of the currency. Fundamental information is supposed to have a permanent effect on currency prices.

Inventory or liquidity effects refer to information about transfers of unwanted currency positions between market-makers. For instance, if a market-maker A has to absorb a large stock of currencies from a market-maker B, the market-maker A will bear more risks (mainly liquidity and valuation risks). As a result, the market-maker A will ask a higher risk premium (hence a lower price) to buy the currencies of market-maker B. This risk premium will only have a transitory effect on the price of the currency since it will disappear after the trade

\(^{27}\) Recently, Carlini et al. (2010) show that in the long run (about 5 years), the cointegration relationship between order flows and stock prices is not significant. However by using more suitable tools, they show that order flows and stock prices are fractionally cointegrated or even still cointegrated if we correct order flows by the volumes of transactions in the market.
between the two market-makers. Thus inventory effects only have transitory effects on currency prices.

Portfolio balance effects relates to agents’ decisions independently of fundamental movements. For example, an import-export firm can operate in the market to convert foreign currencies into domestic currencies independently of fundamental movements. The effect of portfolio balance is assumed to be permanent on currency prices.

A lot of studies have analysed the informational content of order flows. The literature is split between two separate views: the strong flow centric view and the weak flow centric view.

The strong flow centric view states that order flows contain in majority fundamental information. Order flows are correlated with news about exchange rate fundamentals and have thus a permanent effect on currency prices (Ito et al. (1998), Rime (2000), Evans and Lyons (2001, 2002a, 2002b, 2005a, 2008), Love and Payne (2004), Marsh and O’Rourke (2005)).

Love and Payne (2004) base their study on intraday interdealer order flows on the euro/dollar, dollar/pound and pound/euro, from the September 28, 1999 to July 24, 2000. They show that “even information that is publicly and simultaneously released to all market participants is largely impounded into prices via the key micro-level price determinant - order flow”. Love and Payne find that between a half and two-thirds of price relevant information is incorporated into prices via order flows.

Marsh and O’Rourke (2005) use daily customer order flows from August 2002 to June 2004 on bilateral exchange rates between the dollar, the euro, the pound and the yen. They show that inventory effects play a minor role in the informational content of order flows. A major role is attributed to fundamental effects. Particularly, when decomposing order flows by types of clients, they show that coefficients associated to leveraged firms such as hedge funds are very large compared to other flows (such as flows coming from unleveraged firm (mutual funds) and non-financial corporations (multinationals)). They conclude that flows coming from leveraged funds are more informative about fundamentals than flows coming from other customers.

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28 The view of Marsh and O’Rourke (2005) may be confirmed by Corsetti et al. (2001) who claim that a lot of operators believe that hedge funds have an informational advantage relative to the rest of the market concerning asset prices. However another interpretation of the high coefficients associated to order flows coming from hedge funds could be related to the fact that hedge funds speculate aggressively and thus produce huge movements in the market and hence in currency prices. Therefore order flows from hedge funds would be more
Evans and Lyons (2008) estimate an intraday model using interdealer order flows on the deutschemark/dollar market from May 1 to August 31, 1996. They show that roughly two-thirds of the total effect of macro news on the deutschemark/dollar exchange rate is transmitted via order flows. They claim that order flows contribute significantly to changing currency prices at all times, but that they contribute more to changing prices immediately after news arrivals about fundamentals.

Rime, Sarno and Sojli (2010) uses daily interdealer order flows for the euro, the pound and the yen against the dollar between February 13, 2004 and February 14, 2005. They argue that news about macroeconomic fundamentals are important determinants of order flows. They find that “order flow is intimately linked to both news on fundamentals and to changes in expectations about these fundamentals”.

According to the weak flow centric view, order flows do not transmit private information about fundamentals in currency prices. Rather, order flows convey information about liquidity effects, temporary preferences and other demand shocks. Order flows have thus a transitory effect on asset prices. Evidence for the weak flow centric view is based on results provided by econometric analyses as well as survey studies.

Concerning survey studies, Cheung, Chinn and Marsh (2004) base their analysis on a sample of UK-based foreign exchange dealers in March/April 1998. They found that after analysing order flows, “traders do not vary their bid-ask spread either very often or for some of the reasons thought important in the microstructure literature”. Microstructure theory suggests that three main factors can lead traders to change their spreads: liquidity effects, portfolio balance effects and fundamental information. Cheung et al. (2004) add that “traders were asked their reasons for changing their quoted spreads from the market convention and results suggest that the liquidity effect is dominant. This was confirmed in conversations with traders”.

In the same vein, Gehrig and Menkhoff (2006) sent questionnaires to professional market participants in Germany in July 1992. They show that “flows are more informative about semifundamental private information. In other words, order flows contain information about short-term trading objectives or liquidity considerations of other traders that may affect short-term price movements, but that will not affect medium-term asset prices. Such

related to speculative forces rather than to exchange rate fundamentals (Wei and Kim (1998)). Survey results among practitioners reinforce this argument since speculative forces are considered as a major determinant of exchange rates at short run horizons (Cheung and Wong (2000), Cheung and Chinn (2001) and Cheung, Chin and Marsh (2004)).
information may be interim price relevant but irrelevant in the long run”. Gehrig and Menkhoff add that “flow analysis does not seem to be used as a tool to learn about the fundamental information”.


Froot and Ramadorai (2005) analyse a sample of daily institutional investor flows transactions for 18 exchange rates against the US dollar from June 1994 to February 2001. They show that order flows have a transitory impact on exchange rates and do not convey information about macroeconomic fundamentals. “Flows appear to be bound up with transitory currency under- and overreactions, but unrelated to the permanent component of exchange rate surprises. Yet, these exchange rate surprises are strongly related to important fundamental variables, as predicted by theory”.

Berger et al. (2008) analyse monthly interdealer order flows from January 1999 to December 2004 on the euro/dollar and the yen/dollar exchange rates. Their analysis points to an important role for liquidity effects in the relationship between order flows and exchange rates. They provide evidence that the relationship between order flows and exchange rates is strong at daily and weekly frequencies but weakens significantly from monthly frequencies.

Chinn and Moore (2008) analyse monthly interdealer order flows from January 1999 to January 2007 for the dollar/euro and dollar/yen exchange rates. They build an exchange rate model based on a combination of the traditional monetary model of exchange rate and the Evans-Lyons microstructure approach. They show that “cumulative order flow tracks liquidity shocks and provides the ‘missing link’ to augmenting the explanatory power of conventional monetary models”.

The present paper defends the idea that order flows contain information from both the strong and the weak flow centric views; but not solely. The article investigates inside the black box of order flows to disentangle the types of information contained in order flows. This question is becoming increasingly important as the literature has shifted the black box from understanding exchange rate determination to understanding order flow determination.

We build a theoretical model that considers all the information that market agents can embed in currency prices. Our modelling approach integrates not solely the public and private information as in previous works (Bachetta and van Wincoop (2006) and Evans (2010)) but
also behavioural components affecting customers and dealers’ decisions. Our model thus merges two strands of the literature on exchange rates: behavioural exchange rate models and microstructure models of exchange rate. The global model takes account of heterogeneous agents (Frankel and Froot (1986)), the appearance of rumours (Dominguez and Panthaki (2006)), anchoring effects (Kahneman and Tversky (1974), Osler (2002)), status quo bias (Kahneman and Knetsch (1991), De Grauwe and Grimaldi (2008)) and the characteristics of the trading mechanism peculiar to the foreign exchange market (Lyons (1997, 2001)).

4. A theoretical model of the foreign exchange market

4.1 Hypotheses of the model

The model relies on two blocks. The first block is a behavioural model (De Grauwe and Grimaldi (2007)) that provides the characteristics of customers faced by dealers. We assume customers have heterogeneous expectations and are split between two main categories: chartists and fundamentalists. The second block is a microstructure model that represents the trading mechanism of the foreign exchange market. The microstructure model is a simultaneous-trade model that has a decentralised and multiple dealers structure as empirically observed in the foreign exchange market. Our model is notably based on the work of Lyons (1997, 2001) with added elements from Bachetta and van Wincoop (2006). The microstructure model presents three advantages. It first considers interdealer trading that accounts for two-thirds of the trades in the foreign exchange market. Secondly, it takes account of customer order flows as the primary source of private information for dealers. Besides, dealers learn about private information from other dealers through the observation of order flows. Thus the model assumes dealers have access to both public and private information. Thirdly, we suppose risk averse dealers as empirically observed in the foreign exchange market. Table 2 summarizes the timing of the model.
The timing of the model is described as follows. First, customers form their expectations based on their stock of information and their proper models of exchange rate determination. At the same time, dealers set their price based on public information. Customers then ask dealers about their listed price and choose their optimal dealer according to the prices set by dealers.

\[ \text{Since in the foreign exchange market, the bid/ask spread is low due to a high degree of liquidity, we assume a bid/ask spread equal to zero in our model.} \]
Trades in the microstructure model are split into two periods. In the first period the chosen dealers trade with their customers. Such dealers observe the flows coming from customers and try to infer the private information contained in customer order flows. At the end of the first period, dealers trade with other dealers to adjust their stock of risky asset in two ways; either to satisfy the net demand of their customers or to take positions on currencies. In the second period, dealers trade with other dealers to adjust their stock of risky asset in two ways; either to satisfy the net demand by other dealers or to take positions on currencies.

In our model the price of the currency is affected through two channels: a direct channel and an indirect channel. In the direct channel, the price of the currency can change with the arrival of public news even if there is no trade in the market. In the indirect channel, private information coming from customers affect currency prices through order flows\(^3\).

Sections 4.2 and 4.3 describe the structure of the model.

### 4.2 The behavioural model

The behavioural model is based on an heterogeneous agents structure (Frankel and Froot (1986), De Grauwe and Grimaldi (2007)). The model assumes customers can choose between two forecasting rules: a chartist rule and a fundamentalist rule. Fundamentalists forecast exchange rates based on the spread between the current exchange rate \(s_t\) and the fundamental exchange rate \(\overline{s}_t\):

\[
\Delta s_{t+1} = -\alpha_1 (s_t - \overline{s}_t) + \alpha_2 \Psi_t + \varepsilon_t \quad \text{With } \{ \alpha_1, \alpha_2 \} > 0 \quad (1.1)
\]

Thus if the exchange rate is over-appreciated (under-appreciated) relative to its fundamental value, fundamentalists expect the currency to depreciate (appreciate). The parameter \(\alpha_1\) represents the speed at which the exchange rate returns towards its fundamental value. The higher \(\alpha_1\) the stronger the return force of exchange rates towards their fundamental value.
The fundamental exchange rate $\bar{s}_t$ is defined by the interest rate differential between the two countries $(i_t - i_t^*)$:

$$\bar{s}_t = (i_t - i_t^*)$$  \hspace{1cm} (1.2)

With $i_t = i_{t-1} + \epsilon_t$ where $i_t \sim N(0, \sigma_{i_t}^2)$ and $\epsilon_t \sim N(0, \sigma_{\epsilon_t}^2)$; $i_t^* = \alpha^* i_{t-1}^* + \epsilon_t^*$ where $\alpha^* = 0.85$, $i_t^* \sim N(0, \sigma_{i_t^*}^2)$ and $\epsilon_t^* \sim N(0, \sigma_{\epsilon_t^*}^2)$.

Chartists interpolate past trends of exchange rates dynamics to forecast future currency prices:

$$\Delta s_{t+1}^c = \beta_1(s_{t-2}) + \beta_2 \Psi^c_t + \epsilon_t^c \hspace{1cm} \text{With} \{ \beta_1, \beta_2 \} > 0$$  \hspace{1cm} (2)

Thus when the exchange rate has appreciated (depreciated) in the past; chartists expect a further appreciation (depreciation) of the currency. Chartists thus magnify exchange rates movements. The parameter $\beta_1$ represents the degree of interpolation. The higher $\beta_1$, the larger the influence of past exchange rate dynamics on chartists’ forecasts.

The parameters $\Psi_t^f$ and $\Psi_t^c$ represent the effects of collective psychology respectively for fundamentalists and chartists. We assume two definitions for this component. First collective psychology is defined by the appearance of rumours (Dominguez and Panthaki (2006)) that counter past trends of exchange rate dynamics:

$$\Psi_{i, t} = -\frac{1}{\delta} \sum_{i=1}^{\delta} s_{t-i}$$  \hspace{1cm} (3.1)

Secondly, collective psychology is also materialised by the anchoring effect (Kahneman and Tversky (1974), Osler (2002)). When the exchange rate variation is lower than a constant ($|\Delta s_{t, i}| \leq c$), the exchange rate fluctuates around a threshold value following a stable random walk ($0 < \nu < 1$). Conversely, when the exchange rate variation is higher than a

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[31] The interest rate differential has been filtered by a Hodrick-Prescott filter because we assume that the dynamics of the fundamental exchange rate are smooth over time.
constant then the exchange rate wanders away from its current threshold and reaches a new threshold.

\[
\Psi_{2,t} = \begin{cases} 
    u_s s_{t-1} + \epsilon_t & \text{if } |\Delta s_{t-1}| \leq c \\
    \Lambda + u_s s_{t-1} + \epsilon_t & \text{if } |\Delta s_{t-1}| > c
\end{cases}
\]

(3.2)

With \(0 < \nu < 1\) and \(\Lambda\), a constant

The transition between the two states is driven by the following function:

\[ F = \left(\frac{1}{\nu}\right) s_{t-1} + \epsilon_t \quad \text{(with } \epsilon_t \to N(0, \sigma_{\epsilon}^2)) \]

The weight that market agents attribute to a given rule depends on the profitability of a particular rule. The more profitable a rule, the higher the weight agents attach to this rule. Chartist and fundamentalist weights are defined as:

\[
\omega_{c,t} = \frac{\exp(\gamma \pi_{c,t} ')}{[\exp(\gamma \pi_{c,t} ) + \exp(\gamma \pi_{f,t} )]} \quad \text{and} \quad \omega_{f,t} = \frac{\exp(\gamma \pi_{f,t} ')}{[\exp(\gamma \pi_{c,t} ) + \exp(\gamma \pi_{f,t} )]}
\]

(4)

Where \(\omega_{f,t} + \omega_{c,t} = 1\) and \(0 < \gamma < 1\)

The parameter \(\gamma\) represents the intensity at which agents revise their forecasting rules. When \(\gamma \to \infty\), agents choose the rule which proves to be the most profitable. Conversely, when \(\gamma \to 0\), agents keep the rule they are using and are insensitive to the profitability of this rule. Thus \(\gamma\) can be viewed as a representation of the status quo bias in agents’ behaviour. The status quo bias highlighted by Kahneman and Knetsch (1991) means that when agents use a given rule, they find it difficult to change for a different rule. We assume agents need some time to change their rule \((\gamma = 0,2)\).
The profitability $\pi'_{i,t}$ of each rule is evaluated according to the profit $\pi_{i,t}$ and the risk $\sigma^2_{i,t}$ associated to a given rule:

$$\pi'_{i,t} = \pi_{i,t} - \mu \sigma^2_{i,t} \quad i = c, f$$

(5)

The parameter $\mu$ represents the coefficient of risk aversion (we set $\mu = 5$). The risk associated to a forecasting rule is defined as the variance of the forecasting error:

$$\sigma^2_{i,t} = [E_{t-1}(s_t) - s_d]^2 \quad i = c, f$$

(6)

The profit $\pi_{i,t}$ related to a forecasting strategy is defined as the one-period earnings of investing one unit of domestic currency in the foreign asset:

$$\pi_{i,t} = [s_t(1 + i_t^*) - s_{t-1}(1 + i_d)] \text{sgn}[E_{t-1}(s_t)(1 + i_t^*) - s_{t-1}(1 + i_d)] \quad i = c, f$$

(7)

Where

$$\text{sgn}[x] = \begin{cases} 
1 & \text{if } x > 0 \\
0 & \text{if } x = 0 \\
-1 & \text{if } x < 0 
\end{cases}$$

Thus when agents forecast an appreciation of the foreign currency (an increase in $s_t$) they will invest in the foreign country. If this appreciation is realised then their profit is equal to the appreciation of the foreign currency, adjusted by the interest rate differential. Conversely, if the foreign currency depreciates ($s_t$ decreases) agents will face a loss which equals the depreciation of the foreign currency, adjusted by the interest rate differential.
We assume fundamentals have an influence on exchange rate dynamics in the long run. More precisely, we assume that the external debt exerts a return force on currency prices such that the exchange rate returns towards its equilibrium value in the long run. The dynamics of the domestic (foreign) external debt $d_i$ ($d_i^*$) are defined as:

$$d_i = d_{i-1} + i_id_{i-1} + bc_i(s_{i-1}) = (1 + i_i)d_{i-1} - \theta s_{i-1}$$  \hspace{1cm} (8.1)$$

$$d_i^* = d_{i-1}^* + i_i^*d_{i-1}^* + bc_i^*(s_{i-1}) = (1 + i_i^*)d_{i-1}^* + \theta s_{i-1}$$ \hspace{1cm} (8.2)

With $d_i$ ($d_i^*$), the domestic (foreign) external debt; $i_i$ ($i_i^*$), the domestic (foreign) interest rate; $bc_i$ ($bc_i^*$) the domestic (foreign) current account; $s_{i-1}$, the final realised price of the currency at time $t-1$; $\theta = 0.025$; $d_i \rightarrow N(0,\sigma^2_i)$ and $e_i \rightarrow N(0,\sigma^2_e)$; $d_i^* = d_{i-1}^* + e_i^*$, where $d_i^* \rightarrow N(0,\sigma^2_{d*})$ and $e_i^* \rightarrow N(0,\sigma^2_{e*})$ (initially, we assume $d_0 = 0$).

The stock of debt at time $t$ is therefore equal to the stock of debt at time $t-1$ ($d_{i-1}$), plus the interest rate of the debt ($i_id_{i-1}$) and the current account balance at time $t$ ($bc_i$). The current account is related to the exchange rate dynamics by an inverse relationship. Thus when the domestic currency appreciates, the current account worsens and vice versa. We assume also that fundamentalists do not take account of the effect of the external debt on the exchange rate in their rule. The external debt has here an external effect on exchange rate dynamics. In other words, the external debt influences exchange rate dynamics outside the expectations of chartists and fundamentalists.

The expected exchange rate at time $t+1$ is obtained by aggregating agents’ forecasts in the market:

$$E_i(\Delta s_{t+1}) = \omega_{f,i}E_{f,i}(\Delta s_{t+1}) + \omega_{c,i}E_{c,i}(\Delta s_{t+1}) - \theta(d_{i-1} - d_{i-1}^*)$$

$$\leftrightarrow \hspace{2cm} \Delta s^\text{Market}_{t+1} = \omega_{f,i}(\Delta s^f_{t+1}) + \omega_{c,i}(\Delta s^e_{t+1}) - \theta(d_{i-1} - d_{i-1}^*) + e^\text{Market}_{t+1}$$
\[ \Delta s_{t+1}^{Market} = \omega_{f,t}((-\alpha_1(s_t - \bar{s}_t) + \alpha_2\Psi_t^f) + \omega_{c,t}(\beta_1(s_{t-2}) + \beta_2\Psi_t^c) - \theta(d_t - d_{t-1}) + \epsilon_{t+1} \]  

(9)

With \( \theta = 0.025 \) and initially, \( d_0 = 0 \)

The following rules provide the link between the behavioural model and the microstructure model. Order flows from fundamentalists (\( OF_t^f \)) and chartists (\( OF_t^c \)) are defined as:

\[ OF_t^f = F(\Delta s_{t+1}^f) = n.\omega_{f,t} \Delta s_{t+1}^f \text{ where } OF_t^f \in IN \text{ and } \begin{cases} OF_t^f > 0 & \Delta s_{t+1}^f > 0 \\ OF_t^f = 0 & \Delta s_{t+1}^f = 0 \\ OF_t^f < 0 & \Delta s_{t+1}^f < 0 \end{cases} \quad (10) \]

\[ OF_t^c = F(\Delta s_{t+1}^c) = n.\omega_{c,t} \Delta s_{t+1}^c \text{ where } OF_t^c \in IN \text{ and } \begin{cases} OF_t^c > 0 & \Delta s_{t+1}^c > 0 \\ OF_t^c = 0 & \Delta s_{t+1}^c = 0 \\ OF_t^c < 0 & \Delta s_{t+1}^c < 0 \end{cases} \quad (11) \]

With \( n \), the total number of customers in the market

Therefore, when customers expect an appreciation of the currency, they will buy the currency. Conversely, when customers expect a depreciation of the currency, they will sell the currency. We assume customers select an optimal dealer. Customers willing to buy the risky asset choose the dealer that quotes the minimum price. Conversely, customers willing to sell the risky asset choose the dealer that quotes the maximum price. The total amount of customer order flows at time \( t \) is given by:

\[ OF_{t,\text{customers}} = \omega_{f,t} OF_t^f + (1 - \omega_{f,t}) OF_t^c \quad (12) \]
Table 3 decomposes the various types of information contained in the behavioural model.

### Table 3: Decomposition of the information contained in the behavioural model

<table>
<thead>
<tr>
<th>Public Fundamental Information</th>
<th>Public Psychological Information</th>
<th>Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_t, \bar{s}_t, i_t, i_t^<em>, d_t^</em>, d_t^<em>, bc_c, bc_c^</em>$</td>
<td>$\Psi_t^f$</td>
<td>$\varepsilon_t^f$</td>
</tr>
<tr>
<td>Chartist Rule</td>
<td>$s_{t-2}$</td>
<td>$\Psi_t^c$</td>
</tr>
</tbody>
</table>

The behavioural model contains four types of information: public fundamental information, private fundamental information, public psychological information and private psychological information.

Public fundamental information ($s_t, \bar{s}_t, i_t, i_t^*, d_t^*, d_t^*, bc_c, bc_c^*$) deals with information concerning macroeconomic fundamentals. Every agent has access to public fundamental information.

Private fundamental information regroups information about fundamentals that have been analysed or processed by agents. The terms $\alpha_1(s_t - \bar{s}_t)$ and $\beta_1(s_{t-2})$ describe the model of exchange rate determination in which agents believe. They are related to the internal psychology of agents.

Public psychological information ($\Psi_t^f$ and $\Psi_t^c$) relates to information about market psychology (or market agents’ behaviours) that can be observed by every agent. This type of information is associated to the external psychology of agents and can be illustrated by anchoring effects or incoming rumours.

Private psychological information ($\alpha_2\Psi_t^f$ and $\beta_2\Psi_t^c$) defines the weight attributed by customers to the psychological component of exchange rate. Intuitively, this weight defines the degree of rationality of agents. Agents bereft of any psychological component will be considered as more rational than agents who attribute a high weight to this component.

The parameter $\varepsilon_t^f$ ($\varepsilon_t^c$) is a white noise that represents unexpected news or unexpected behaviours by fundamentalists (chartists). Therefore, the noise parameters can represent either public information or private information about fundamentals or customers’ behaviours.
4.3 The microstructure model

We follow Lyons (1997) and model the trading mechanism of the foreign exchange market with a simultaneous-trade model with multiple dealers. We assume the existence of \( m \) dealers in the market. In this model, dealers are not solely market-makers (they match the supply and demand of currencies); they are also speculators (they take positions on currencies).

4.3.1 Period 1 of the microstructure model

Given their information set (public and private signal), dealers set their currency price based on the following rule:

\[
P_{0,t}^i = s_{t-1} + \xi_{0,t}^i + \epsilon_{Market}^i
\]  

(13)

Where \( \xi_{0,t}^i \rightarrow iidN(\mu;\sigma_\xi^2) \), \( \epsilon_{Market}^i \rightarrow iidN(\mu;\sigma_\epsilon^2) \) and \( i = 1,\ldots,m \)

The first price \( P_{0,t}^i \) set by dealers includes public information about fundamentals \( s_{t-1} \), private information proper to the dealer \( \xi_{0,t}^i \) and unexpected news about fundamentals \( \epsilon_{Market}^i \). The term \( \xi_{0,t}^i \) is interpreted as a private signal that dealers hold concerning the future exchange rate dynamics. This private signal induces a difference among prices listed by dealers.

Equation (13) is the start of the direct channel of news incorporation into currency prices. Indeed, the price of the currency can change with the arrival of public news (through the terms \( s_{t-1}, \xi_{0,t}^i, \epsilon_{Market}^i \)) even if there is no trade between customers and dealers in the market (\( OF_t^{customers} = 0 \)).

Once dealers set their price, customers select their optimal dealer. Customers willing to buy the risky asset will choose the dealer that quotes the minimum price. Conversely, customers willing to sell the risky asset will choose the dealer that quotes the maximum price.
If \( OF_i^f > 0 \), fundamentalists trade with dealer \( i \) such that:
\[
P_i^f = \min \left\{ P_0^i \right\} \quad \forall i \in m
\]
\[
P_0^i = \max \left\{ P_0^i \right\} \quad \forall i \in m
\]

If \( OF_i^c > 0 \), chartists trade with dealer \( i \) such that:
\[
P_i^f = \min \left\{ P_0^i \right\} \quad \forall i \in m
\]
\[
P_0^i = \max \left\{ P_0^i \right\} \quad \forall i \in m
\]

Notice that some dealers receive orders flows from customers while other dealers do not. We thus face two cases. On the one hand, dealers that receive orders flows from customers have access to private information and include this information into their quoted price. On the other hand, dealers that do not receive any orders from customers do not have access to private information. Such dealers will learn about private information through the hot potato effect \( i.e. \) through interdealers order flows in period 2. Therefore customer order flow is the source of information asymmetry in this model.

When dealers receive order flows from customers, they will try to infer the private information contained in these order flows. If dealers receive positive (negative) customer order flows \( OF_i^f + OF_i^c > 0 \) (\( OF_i^f + OF_i^c < 0 \)), they will include a positive (negative) private signal \( \xi_{1,i}^f \) (\( \xi_{1,i}^c \)) in their quoted price \( P_{1,i}^f \). If dealers receive no customer order flows (\( OF_i^f = OF_i^c = 0 \)), they receive no private signal from customers. We assume that the signal \( \xi_{1,i} \) extracted by dealers from customer order flows follows a white noise process. The quoted price \( P_{1,i}^f \) by dealers after trades with customers is thus given by:

\[
P_{1,i}^f = P_{0,i}^f + \begin{cases} 
\xi_{1,i}^f & OF_i^f + OF_i^c > 0 \\
\xi_{1,i}^c & OF_i^f + OF_i^c < 0 \\
0 & OF_i^f + OF_i^c = 0 
\end{cases}
\]

Where \( \xi_{1,i} \to iidN(\mu; \sigma_\xi^2) \) and \[ \begin{align*}
\xi_{1,i}^f & \in [0,1] \\
\xi_{1,i}^c & \in [-1,0]
\end{align*} \]
Dealers quote their price simultaneously and independently. Quoted price are observable and available to all dealers. Each quote is a single price at which the dealer agrees both to buy and sell. Equation (15) is the start of the indirect channel in which dispersed or private information coming from customers affect currency prices through order flows, based on the term $\xi_{1,t}$.

We define the demand for the risky asset by dealer $i$ or the desired stock of currency in period 1 for dealer $i$ $D_{1,t}^i$ by:

$$D_{1,t}^i = a_1 s_{t-1} + a_2 \xi_{0,t}^i + a_3 H_{1,t}^i - a_4 \bar{P}_t$$

With $a_3 = \frac{y_t}{\mu_d}$, $0 < \{a_1, a_2, a_4\} < 1$, $a_1 > a_4$ and $\bar{P}_t = \frac{1}{m} \sum_{i=1}^m P_{i,t}^1$.

The following three paragraphs help understanding the structure of equation (16).

First, dealers have access to both public and private information sources. Their demand for the risky asset depends on public information $s_{t-1}$ (the higher $s_{t-1}$, the more appreciated the value of the stock of risky asset, the higher the demand for the risky asset); private information coming from customer order flows $\xi_{0,t}^i$ (the higher $\xi_{0,t}^i$, the higher the incentive for dealers to invest in the risky asset); the private signal that dealers hold on the future exchange rate dynamics $\xi_{0,t}^i$ (the higher $\xi_{0,t}^i$, the higher the incentive for dealers to invest in the risky asset); and the average price of the risky asset set by dealers in period 1 $\bar{P}_t$ (the higher $\bar{P}_t$, the lower the demand for the risky asset).

Secondly, dealers are also speculators in this model. They benefit from the information contained in their received customer order flows to take speculative positions on the risky asset. The term $y_t$ takes account of the speculative dimension of dealers. This term acts as a leverage effect on the demand for currencies by dealers. We assume that the willingness to buy or sell currencies for dealers depends on the amount bought or sold by their customers. If dealers receive an amount of customer order flows higher than the average amount of order flows received in the past from customers (\( |OF_{\text{customer}}^t| > |\bar{OF}_{\text{customer}}^t| \)), dealers will buy a higher
amount of currencies ($\gamma^i > 1$). Conversely, if dealers receive an amount of customer order flows lower than the average amount of order flows received in the past from customers ($\left| OF^\text{customer}_t \right| < \left| \overline{OF}^\text{customer}_t \right|$), dealers will buy a lower amount of currencies ($0 < \gamma^i < 1$). The same reasoning holds when selling currencies. Thus, the willingness to buy/sell currencies by dealer $i$ is defined by the term $\gamma^i$ such that:

$$
\gamma^i = \begin{cases} 
0 < \gamma^i < 1 & \text{if } \frac{\left| OF^\text{customer}_t \right|}{\left| \overline{OF}^\text{customer}_t \right|} < 1 \\
\gamma^i > 1 & \text{if } \frac{\left| OF^\text{customer}_t \right|}{\left| \overline{OF}^\text{customer}_t \right|} > 1 
\end{cases}
$$

(17)

Thirdly, the parameter $\mu_d$ represents the degree of risk aversion for dealers: if $\mu_d < 1$, dealers are risk lover; if $\mu_d > 1$, dealers are risk averse; if $\mu_d = 1$, dealers are risk neutral.

Beyond their role of speculators, dealers are also market-makers. They match the demand and supply of currencies by customers. We define the dealer $i$ trading rule $T^i_{1,t}$ in period 1 as:

$$
T^i_{1,t} = D^i_{1,t} + C^i_{1,t} + \mathbb{E}\left[ T^i_{1,t} / \Omega^i_{1,t} \right]
$$

(18)

The term $T^i_{1,t}$ depends on $D^i_{1,t}$, $C^i_{1,t}$ and $\mathbb{E}\left[ T^i_{1,t} / \Omega^i_{1,t} \right]$. The term $T^i_{1,t}$ defines the necessary amount of order flows that dealers have to pass to other dealers to satisfy their own demand of risky asset given orders coming from customers and given orders coming from other dealers. The term $C^i_{1,t}$ represents customer order flows addressed to dealer $i$. Customers will be net buyers if $C^i_{1,t} > 0$. Conversely, customers will be net sellers if $C^i_{1,t} < 0$. Obviously, $C^i_{1,t} = OF^f_t + OF^c_t$. If the dealer does not receive any orders from customers, then $OF^f_t = OF^c_t = 0$ and $C^i_{1,t} = 0$. As dealers’ trades are simultaneous, $\mathbb{E}\left[ T^i_{1,t} / \Omega^i_{1,t} \right]$ represents the order flows coming from other dealers and expected by dealer $i$, at time $t$. We define $\mathbb{E}\left[ T^i_{1,t} / \Omega^i_{1,t} \right]$ as: $\mathbb{E}\left[ T^i_{1,t} / \Omega^i_{1,t} \right] = T^i_{2,t-1} + \epsilon^i_t$. The term $T^i_{2,t-1}$ represents the net flows received by dealer $i$ from other dealers in period 2, at time $t-1$. The term $D^i_{1,t}$ is the desired stock of currencies by dealer $i$.

---

32 Initially, we set $T^i_{2,t-1} = 0$ and $\mathbb{E}\left[ T^i_{1,t} / \Omega^i_{1,t} \right] = \epsilon^i_t$; with $\epsilon^i_t \sim iidN(\mu, \sigma^2)$. 

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The definition of order flows by dealer $i$ in period 1 is given by:

$$T_{i,t}^i = D_{i,t}^i + C_{i,t}^i + E[ T_{i,t}^j / \Omega_{i,t}^j ]$$  \hspace{1cm} (19)$$

$$\leqslant \Rightarrow T_{i,t}^i = a_1 s_{i,t} + a_2 \xi_{0,t}^i + a_3 \xi_{1,t}^i - a_4 t_{i,t}^j + (OF_{i,f}^i + OF_{i,c}^i) + T_{2,t-1}^j + \varepsilon^i_t$$  \hspace{1cm} (20)$$

Dealers then choose to trade with their optimal dealer. Buyer dealers will buy currencies at the lowest price. Seller dealers will sell currencies at the highest price:

$$\begin{cases} T_{i,t}^i > 0 \quad \text{dealer } i \text{ trades with dealer } j \text{ such that:} & P_{1,t}^i = \min\{P_{1,t}^j\} \quad \forall j \in m, i \neq j \\ T_{i,t}^i < 0 \quad & P_{1,t}^i = \max\{P_{1,t}^j\} \quad \forall j \in m, i \neq j \end{cases}$$  \hspace{1cm} (21)$$

The net cumulated interdealer order flows in period 1 $V_{1,t}$ amount to:

$$V_{1,t} = \sum_{i=1}^{m} T_{1,t}^i$$  \hspace{1cm} (22)$$

As in Lyons (1997), we assume that the initial demand of risky asset by dealer $i$ (or equivalently the initial desired stock of risky asset for dealer $i$) $D_{i,t}^i$ is equal to zero.
4.3.2 Period 2 of the microstructure model

In period 2, dealers trade between each other. Their trades are based on private information contained in order flows. Dealers start to revise their quoted price given their updated stock of information. We assume that the price quoted by dealers in period 2 is linked to the latest market quote $P_{1,t}$ and to the net interdealer order flows in period 1 $V_{1,t}$. This assumption gives more stability to the model. We hence define the price quoted by dealer $i$ in period 2 as:

$$P_{2,t}^{i} = P_{1,t}^i + \begin{cases} \xi_{2,t}^{i+} & V_{1,t} > 0 \\ \xi_{2,t}^{i-} & V_{1,t} < 0 \\ 0 & V_{1,t} = 0 \end{cases}$$

(23)

Where $\xi_{2,t}^{i} \sim iidN(\mu^{i}; \sigma^{2i})$ and $\{\xi_{2,t}^{i+} \in [0,1], \xi_{2,t}^{i-} \in [-1,0]\}$

Therefore if the net cumulated interdealer order flows in period 1 $V_{1,t}$ is positive (negative), then the demand by dealers for the risky asset increases (decreases), and thus dealers will increase (decrease) their quoted price for the currency in period 2.

Once dealers have set their price in period 2, they define their net demand for currencies in period 2 $D_{2,t}^{i}$ according to the following relationship:

$$D_{2,t}^{i} = \frac{1}{\mu_d} \left( b_1 s_{1,t-1} + b_2 V_{1,t} - b_3 \sum_{j=1}^m P_{2,t}^j \right) + \frac{\gamma^{i}}{\mu_d} \xi_{2,t}^{i}$$

(24)

With $\sum_{j=1}^m P_{2,t}^j \geq 0 \<? b_1, b_2, b_3<1 \text{ and } b_1 > b_3$
And \( \xi_{3,i}^{t} = \begin{cases} \xi_{3,i}^{t} & \text{if } \overline{T}_{i,1}^{t} > \overline{T}_{i,2}^{t} \\ \xi_{3,i}^{t} & \overline{T}_{i,1}^{t} < \overline{T}_{i,2}^{t} \\ 0 & \overline{T}_{i,1}^{t} = \overline{T}_{i,2}^{t} \end{cases} \), where \( \xi_{3,i}^{t} \rightarrow iidN(\mu, \sigma_{\xi}^{2}) \) and \( \xi_{3,i}^{t} \in [0,1] \) \((25)\) 

With \( \overline{T}_{i,1}^{t} = \frac{1}{T} \sum_{t=1}^{T} T_{i,1}^{t} \) 

The following three paragraphs help understanding the structure of equation (24).

First, the demand for currencies in period 2 by dealer \( i \) \( D_{2,i} \) depends on public information \( s_{t,i} \) (the higher \( s_{t,i} \), the more appreciated the value of the stock of risky asset, the higher the demand for the risky asset); interdealer order flows \( V_{1,i} \) observed by dealers at the end of period 1 (the higher \( V_{1,i} \), the higher the demand for the risky asset by dealers in period 1, the more appreciated the value of the stock of risky asset, the higher the demand for the risky asset by dealers in period 2); the average price set by dealers in period 2 \( \overline{P}_{2,i} \) (the higher \( \overline{P}_{2,i} \), the lower the demand for the risky asset); private information \( \xi_{3,i}^{t} \) coming from dealers that received customer order flows in period 1 (the higher \( \xi_{3,i}^{t} \), the higher the incentive for dealers to invest in the risky asset).

Thus, in period 2, dealers infer private information \( \xi_{3,i}^{t} \) from customer order flows through order flows coming from dealers that had traded with customers in period 1. Recall that the only way dealers can learn about private information from other dealers is through the observation of interdealer order flows coming from other dealers.

The term \( T_{i,1}^{t} \) in equation (25) represents order flows coming from other dealers to dealer \( i \). As a matter of facts, if \( |T_{i,1}^{t}| < |\overline{T}_{i,1}^{t}| \) then order flows coming from other dealers to dealer \( i \) are lower than the average amount of past order flows coming from other dealers to dealer \( i \). This case means that the demand of risky asset by other dealers is decreasing. As a result, dealer \( i \) will expect a depreciation of the currency \( (\xi_{3,i}^{t} = \xi_{3,i}^{t-1}) \). The demand of currency by dealer \( i \) will thus decrease (and vice versa when \( |T_{i,1}^{t}| > |\overline{T}_{i,1}^{t}| \)).
Secondly, dealers are also speculators. The term $\gamma^i_2$ takes account of the speculative dimension of dealers. This term acts as a leverage effect on the demand for currencies by dealers. We assume the willingness to buy or sell the risky asset for dealers depends on the amount bought or sold by their dealers’ counterparts. Therefore, if dealer $i$ receives an amount of order flows from other dealers higher than the average amount of order flows received in the past ($|T^i_{1,t}| > |T^i_{2,t}|$), dealer $i$ will buy a higher amount of risky asset ($\gamma^i_2 > 1$). Conversely, if dealer $i$ receives an amount of order flows from other dealers lower than the average amount of order flows received in the past ($|T^i_{1,t}| < |T^i_{2,t}|$), dealer $i$ will buy a lower amount of risky asset ($0 < \gamma^i_2 < 1$). The same reasoning holds when selling currencies. The term $\gamma^i_2$ defines the willingness to buy/sell the risky asset for dealer $i$:

$$\gamma^i_2 = \begin{cases} 
0 < \gamma^i_2 < 1, & \text{if } |T^i_{1,t}| < |T^i_{2,t}| \\
\gamma^i_2 > 1, & \text{if } |T^i_{1,t}| > |T^i_{2,t}| 
\end{cases} \quad (26)$$

Thirdly, the parameter $\mu_d$ represents the degree of risk aversion of dealers: if $\mu_d < 1$, dealers are risk lover; if $\mu_d > 1$, dealers are risk averse; if $\mu_d = 1$, dealers are risk neutral.

The trading rule for dealer $i$ in period 2 is defined as follows:

$$T^i_{2,t} = D^i_{2,t} - D^i_{1,t} + T^i_{1,t} + E[T^i_{1,t} / \Omega^i_{1,t}] + E[T^i_{2,t} / \Omega^i_{2,t}] \quad (27)$$

The term $T^i_{2,t}$ depends on $D^i_{1,t}$, $D^i_{2,t}$, $T^i_{1,t}$, $E[T^i_{1,t} / \Omega^i_{1,t}]$ and $E[T^i_{2,t} / \Omega^i_{2,t}]$. The flows ($D^i_{2,t} - D^i_{1,t}$) represent a revision by dealer $i$ of the amount invested in currencies or equivalently a revision of their desired stock of currency. The term ($D_{2,t}^i - D_{1,t}^i$) is interpreted as an inventory effect. The inventory effect in turn triggers the hot potato effect. Hence agents pass their undesired positions to other dealers in the market through the term $T_{2,t}^i$. Trades in period 2 depend also on the error made by dealer $i$ on the expected flows coming from other
dealers in period 1 \((T_{1j}^{i} - E[T_{1j}^{i} / \Omega_{1j}^{i}])\) and on the expected order flows to be received in period 2 \((E[T_{2j}^{i} / \Omega_{2j}^{i}])\).

The expected flows from other dealers \(j\) by dealer \(i\) is equal to the flows received by dealer \(i\) in period 1, plus a noise:

\[
E[T_{2j}^{i} / \Omega_{2j}^{i}] = \sum_{j=1}^{m-1} T_{1j}^{i} + \epsilon_{i}^{j} \quad \text{With } \epsilon_{i}^{j} \rightarrow iidN(\mu_{\epsilon}^{i}; \sigma_{\epsilon}^{i})
\] (28)

Therefore, the definition of order flows by dealer \(i\) in period 2 \(T_{2j}^{i}\) is given by:

\[
T_{2j}^{i} = \frac{1}{\mu_{d}} (b_{1}s_{j,1} + b_{2}V_{j,1} - b_{3} \bar{F}_{2j,1}) + \frac{\gamma_{j}^{i}}{\mu_{d}} \sigma_{j}^{i} - (T_{2j-1}^{i} + T_{1j}^{i} + \epsilon_{i}^{j}) + \left( \sum_{j=1}^{m-1} T_{1j}^{i} + \epsilon_{i}^{j} \right)
\] (29)

Dealers then choose to trade with their optimal dealer. Buyer dealers will buy currencies at the lowest price. Seller dealers will sell currencies at the highest price:

\[
\begin{array}{ll}
\text{If } & T_{2j}^{i} > 0, \text{ dealer } i \text{ trades with dealer } j \text{ such as: } \\
& P_{2j}^{i} = \text{Min}\{P_{2j}^{j}\} \quad \forall j \in m, i \neq j \\
& P_{2j}^{i} = \text{Max}\{P_{2j}^{j}\} \quad \forall j \in m, i \neq j
\end{array}
\] (30)

The net cumulated interdealer order flows in period 2 \(V_{2j}\) amount to:

\[
V_{2j} = \sum_{i=1}^{m} T_{2j}^{i}
\] (31)

The final value \(F_{i}\) of the risky asset in period 2 is given by:

\[
F_{i} = \frac{1}{m} \sum_{i=1}^{m} P_{2j}^{i} = s_{i}
\] (32)

---

34 The term \((T_{1j}^{i} - E[T_{1j}^{i} / \Omega_{1j}^{i}])\) represents the effective flows coming to dealer \(i\) from other dealers in period 1.
4.4 Stochastic simulations of the model

We simulate the model over 3000 periods with 50 dealers in the market. Figure 1.1 shows the dynamics of the simulated exchange rate, the fundamental exchange rate and the proportion of fundamentalists in the market. Figure 1.2 shows the relative profitability of the chartist and the fundamentalist rules and the proportion of fundamentalists.

**Figure 1.1: Simulated exchange rate, fundamental exchange rate and proportion of fundamentalists**

![Graph showing simulated exchange rate, fundamental exchange rate, and proportion of fundamentalists.]

**Figure 1.2: Relative profitability of chartist and fundamentalist rules and proportion of fundamentalists**

![Graph showing relative profitability of chartist and fundamentalist rules and proportion of fundamentalists.]

NB: For figure 1.1, the black line represents the simulated exchange rate $F$ (left scale); the grey line represents the fundamental exchange rate $\tilde{F}$ (left scale); the blue margins represent periods in which fundamentalists dominate the market (right scale). For figure 1.2, the black line represents the relative profitability between the chartist rule and the fundamentalist rule $(\pi'_c - \pi'_f)$; the blue margins represent periods in which fundamentalists dominate the market (right scale).

From figure 1.1, we observe that in the short run, there is a persistent gap between the simulated exchange rate $F$ and its fundamental value $\tilde{F}$. Over the long run, the simulated exchange rate returns towards its fundamental value. The heterogeneity of behaviours in the market or equivalently the use of different models by agents explains the disconnection of the market exchange rate from its fundamental value. When chartists dominate the market (white margins), the exchange rate wanders away from its fundamental value. Conversely, when fundamentalists dominate the market (blue margins), the exchange rate returns towards its fundamental value.

As shown in figure 1.2 the domination of a given type of agent in the market depends on the profitability of the agent’s rule. If the profitability of the chartist rule is higher than the profitability of the fundamentalist rule, chartists dominate the market. Conversely, when the fundamentalist rule becomes more profitable than the chartist rule, fundamentalists dominate the market.

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35 The values for the exogenous parameters are available in appendix F, table F.
Figure 2.1 and 2.2 show the dynamics of the simulated exchange rate with respectively the dynamics of customer order flows and the ones of interdealer order flows.

**Figure 2.1: Simulated exchange rate and customer order flows**

**Figure 2.2: Simulated exchange rate and interdealer order flows**

NB: For figure 2.1, the black line represents the simulated exchange rate $F$ (left scale); the dark grey line represents customer order flows $OF_{\text{customer}}$ (right scale). For figure 2.2, the black line represents the simulated exchange rate $F$ (left scale); the light grey line represents interdealer order flows $V_2$ (right scale).

Figures 1.1, 2.1 and 2.2 show that the theoretical model replicates three stylised facts observed empirically in the foreign exchange market.

First, simulations in figures 2.1 and 2.2 confirm the close link between exchange rate dynamics and cumulative order flows at short and long run horizons. The coefficient of correlation between the simulated exchange rate and customer order flows (respectively interdealer order flows) amounts to 99.47% (respectively 98.42%). This result comes in line with the empirical observations of microstructure theorists (Lyons (2001), Evans and Lyons (2001, 2002a, 2002b), Rime et al. (2010)).

Secondly, the amount of interdealer order flows is larger than the amount of customer order flows. This fact is due to the hot potato effect. This phenomenon describes the fact that with the incoming stock of new information, dealers revise their demands of currencies. Revisions in their willing stock of currencies induce inventory imbalances or undesired stock of currencies. Dealers get rid of these inventory imbalances by passing them to other dealers. As a result, inventory imbalances are passed from dealers to dealers in the market. These trades of unwanted positions inflate the amount of order flows between dealers in the market. These trades further magnify the amount of interdealer order flows relative to the initial amount of customer order flows. In the model, the hot potato effect appears in period 2 where dealers trade between each other. The hot potato effect is defined through the term $T_{2,t}^i$ by the inventory effect or equivalently the revision of undesired positions on currencies ($D_{2,t}^i - D_{1,t}^i$).
Such inventory effects are an important feature of microstructure models willing to represent the trading mechanism of the foreign exchange market. Indeed, empirically, the hot potato effect represents 60% of the trades between agents in the foreign exchange market (Lyons (2001)).

Thirdly, figures 1.1, 2.1 and 2.2 show that in the short run, the simulated exchange rate is disconnected from its fundamental value but not from order flows. However, in the long run, the simulated exchange rate returns towards its fundamental value and is still highly correlated with order flows. This result comes in line with the one from the theoretical work by Bachetta and van Wincoop (2006) and the empirical work by Berger et al. (2008).

5. Further results from the theoretical model of the foreign exchange market

5.1 Is the foreign exchange market intrinsically inefficient?

According to Fama (1965), a market is considered as informationally efficient if the price of an asset is equal to its fundamental value, given all available information at time $t$. In our theoretical model, we define the fundamental value of the exchange rate $\bar{s}$ by the interest rate differential between the domestic and the foreign country:

$$\bar{s} = (i_t - i_t^*)$$ (33)

Figure 3 shows the dynamics of the market exchange rate $s_{\text{market}}$, the fundamental exchange rate $\bar{s}$ and the simulated exchange rate $F$ or equivalently the final listed exchange rate.
Figure 3: Simulated exchange rate ($F$), market exchange rate ($s_{\text{market}}$) and fundamental exchange rate ($\bar{s}$)

NB: The black line represents the simulated exchange rate or equivalently the final exchange rate quoted by dealers ($F$); the dark grey line represents the fundamental exchange rate ($\bar{s}$); the light grey line represents the market exchange rate expected by customers ($s_{\text{market}}$).

The market exchange rate $s_{\text{market}}$ (which we label as the behavioural exchange rate) fluctuates around its fundamental value $\bar{s}$. In some periods, it wanders away while returning to its fundamental value at other periods. The final exchange rate quoted by dealers $F$ (which we label as the microstructure exchange rate) appears more disconnected from the fundamental value than the market exchange rate $s_{\text{market}}$.

Therefore, the final price quoted in the foreign exchange market $F$ does not reflect the fundamental value $\bar{s}$ of the asset. The behavioural exchange rate and the microstructure exchange rate are different from the fundamental exchange rate. Thus the foreign exchange market can be considered as intrinsically inefficient: the final quoted value of the exchange rate by dealers is not equal to the fundamental value of the exchange rate. Indeed, the original information that determines the fundamental exchange rate is distorted through agents’ behaviours and through the quotation process of the final currency price $F$. This information distortion appears at two levels in the model.

On the one hand, information is distorted by the fact that agents have heterogeneous expectations in the market. We label this distortion of information as behavioural noise. The behavioural noise or the behavioural component of the final exchange rate $F$ can be split in two factors: internal factors and external factors.

Internal factors represent individual psychology (or psychological factors observable at agents’ level). Such factors include individual preferences (risk aversion, proper interpretation of news, overreaction to news, learning effects, etc.) but also specific rules used by individuals (heuristics, heterogeneous expectations, technical models, fundamental models,
etc.). For example, in our model, internal factors are represented by agents’ heterogeneous expectations or agents’ heterogeneous models (chartist and fundamentalist rules).

External factors represent global psychology (or psychological factors observable at a global level in the market). They include rumours, mimetism and conventions that influence the market. In the model, external factors are considered through the appearance of rumours (equation (3.1)) and also through the anchoring effect (equation (3.2)).

Internal and external psychological factors represent the behavioural biases from the rational expectations hypothesis (such as anchoring biases, overreaction, etc.). Indeed, REH models assume the existence of a representative agent that has homogenous expectations and that is bereft of any psychological dimension.

On the other hand, information is also distorted by the trading mechanism peculiar to the foreign exchange market. This point was already highlighted by Lyons (1998). We label this information distortion as microstructure noise. The microstructure noise or the microstructure component of the final exchange rate $F$ is induced by two factors: the noise brought by the interpretation of private information by dealers and also the noise brought by the passing of undesired positions.

The noise brought by the interpretation of private information by dealers is illustrated as follows. Recall that only a minority of dealers have access to private information. Assume that private information from customers comes to a dealer that offers the optimal price for customers. Then the chosen dealer has to infer the information contained in order flows coming from customers. The dealer provides a more or less correct interpretation of the original private information contained in customer order flows. The dealer’s interpretation of the information is shaped notably by his/her risk aversion and also by his/her desired leverage effect\textsuperscript{36}. The dealer will then transmit his/her interpretation of the original private information to another dealer through interdealer order flows. This other dealer will in turn provide a more or less correct interpretation of the information contained in the order flows coming from the first dealer (and hence a more or less correct interpretation of the original private information from the original customer). As a result, if the original private information passes through a large amount of dealers - or equivalently if the hot potato effect is large - then the precision of the original private information is lowered. The final price will be therefore less revealing of

\textsuperscript{36} Hence the strategic or speculative behaviour of the dealer contributes to the distortion of the original information.
the original private information. Hence, the larger the hot potato effect, the higher the information distortion, the lower the efficiency of the foreign exchange market.

The noise brought by the passing of undesired positions works as follows. Recall that independently of the private information received from customers, dealers adjust also their desired positions in the risky asset given their updated stock of information. Although the passing of unwanted positions have a transitory effect on the price of the currency, they act as a noise on interdealer order flows. Indeed, dealers do not know whether order flows coming from other dealers define simply unwanted positions bereft of any private information from customers or if such order flows coming from other dealers contain elements of private information. Hence the passing of unwanted positions act as a noise in the extraction of private information from customer order flows. As a result, the larger the amount of unwanted positions in the market (or equivalently the larger the hot potato effect), the higher the noise in interdealer order flows, the larger the difficulty to extract the original private information provided by customers. Therefore the hot potato effect - trading mechanism peculiar to the foreign exchange market - distorts the original private information provided by customers in the final currency price and hence alters the efficiency of the foreign exchange market.

As a consequence, the conjunction of a behavioural noise (internal factors and external factors) and a microstructure noise (either the interpretation of private information by dealers or the noise brought by the passing of undesired positions) implies that the foreign exchange market is intrinsically inefficient. The incoming information is distorted by agents’ behaviours and by the trading mechanism peculiar to the foreign exchange market.

Note also that the behavioural noise is often considered as larger than the microstructure noise; the microstructure noise being often assumed as negligible. In order to observe this fact properly in the model, one should isolate the microstructure noise peculiar to the trading mechanism of the foreign exchange market from the noise induced by dealers’ behaviours and also from the noise implied by customers’ behaviours. This task goes beyond the scope of this article.
5.2 Towards a resolution of the exchange rate disconnection puzzle?

The exchange rate disconnection puzzle states that the empirical dynamics of currency prices are disconnected from their fundamentals. The disconnection puzzle was highlighted by Meese and Rogoff (1983). They found that traditional exchange rate models based on a linear and symmetric structure offer little explanatory and predictive powers concerning exchange rate dynamics, especially in the short run.

We mentioned previously that the explanatory power of exchange rate dynamics by order flows models far exceeds the one of traditional exchange rate models, especially at short run horizons. As a result, one may wonder whether order flows models of exchange rate provide an answer to the exchange rate disconnection puzzle?

We analyse the relative explanatory power of order flows versus macroeconomic fundamentals by relying on the simulated series from our theoretical model of the foreign exchange market. The simulated exchange rate $F$ is the endogenous variable. We consider as exogenous variables the interest rate differential $(i_t - i_t^*)$ that defines the fundamental exchange rate ($\bar{s}$ in the theoretical model) and interdealer cumulated order flows $X_t$ ($V_2$ in the theoretical model). All series are non-stationary in level but stationary in first difference within the 3000 periods of simulations. Regressions are based on OLS (with Newey-West correction for heteroskedasticity and autocorrelation). Table 4 shows the output of the regressions.

<table>
<thead>
<tr>
<th>Table 4: Empirical tests based on simulated series from the theoretical model of the foreign exchange market</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model 1</strong></td>
</tr>
<tr>
<td>Coefficients</td>
</tr>
<tr>
<td>$\Delta F$</td>
</tr>
<tr>
<td>Coefficients</td>
</tr>
<tr>
<td>$\Delta F$</td>
</tr>
<tr>
<td>Coefficients</td>
</tr>
<tr>
<td>$\Delta F$</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; $p$-values are mentioned in brackets; critical values for the test of Student amount to 1.96 at a 5% confidence level and to 1.64 at a 10% confidence level.

37 See appendix E for stationarity tests.
As expected, table 4 shows that order flows provide a better explanatory power of currency movements than fundamentals. Order flows explain a significant part of the variance of exchange rate dynamics considered in first difference (R² amounts almost at 60 %) contrary to fundamentals (R² is lower than 1 %).

We compare this theoretical result to the empirical fit of order flows models versus traditional models of exchange rate. We rely on the original dataset provided by Evans and Lyons (2002)⁴⁸. Tests are based on the deutschmark/dollar, yen/dollar and pound/dollar at a daily frequency, from May, 1 1996 to August, 23 1996. Order flows considered here are interdealer order flows. Because of non-stationarity, series are considered in first difference. Equations are estimated by OLS (with Newey-West correction for heteroskedasticity and autocorrelation). Table 5 shows the output of the regressions.

### Table 5: Empirical tests based on the original model of Evans and Lyons (2001, 2002)

<table>
<thead>
<tr>
<th>Model 1</th>
<th>(Δs_t = β_0 + β_1 Δ(i_t - 1) + β_2 ΔX_t + ε_t)</th>
<th>Diagnostic Tests</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>(β_0)</td>
<td>(β_1)</td>
</tr>
<tr>
<td>Deutschmark</td>
<td>-3,55x10⁻⁴</td>
<td>9,45x10⁻⁴</td>
</tr>
<tr>
<td>Pound</td>
<td>9,30x10⁻⁶</td>
<td>3,69x10⁻⁷</td>
</tr>
<tr>
<td>Yen</td>
<td>-4,44x10⁻⁴</td>
<td>3,13x10⁻⁵</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 2</th>
<th>(Δs_t = β_0 + β_1 ΔX_t + ε_t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>(β_0)</td>
</tr>
<tr>
<td>Deutschmark</td>
<td>-3,82x10⁻⁴</td>
</tr>
<tr>
<td>Pound</td>
<td>-5,64x10⁻⁴</td>
</tr>
<tr>
<td>Yen</td>
<td>-4,40x10⁻⁴</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 3</th>
<th>(Δs_t = β_0 + β_1 Δ(i_t - 1) + ε_t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>(β_0)</td>
</tr>
<tr>
<td>Deutschmark</td>
<td>-4,40x10⁻⁴</td>
</tr>
<tr>
<td>Pound</td>
<td>-4,72x10⁻⁴</td>
</tr>
<tr>
<td>Yen</td>
<td>-3,99x10⁻⁴</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets ; p-values are mentioned in brackets ; critical values for the test of Student amount to 1,96 at a 5 % confidence level and to 1,64 at a 10 % confidence level.

The theoretical results from table 4 are confirmed in table 5. At daily frequencies, order flows models (model 2 in table 5) provide a better fit of exchange rate dynamics than traditional models of exchange rate (model 3 in table 5). Considering the case of the

⁴⁸ We ask every entity likely to collect order flows but we did not manage to have access to order flows data. The main reason provided by our contacts was that order flows are confidential data.
deutschemark/dollar exchange rate, order flows models provide a coefficient of determination ($R^2$) equal to 65% while the coefficient of determination for traditional models of exchange rate amounts to 5%.

The better fit of order flows models holds not only at short horizons (as shown here for daily frequencies) but also for long run horizons. Indeed, Berger et al. (2008) analyse interdealer order flows from January 1999 to December 2004 on the euro/dollar and the yen/dollar exchange rates. They show that interdealer order flows have a significant impact on exchange rate variations in the short and in the medium run but much less explanatory power for long term exchange rate movements. However, although the explanatory power of order flows models falls in the long run, Berger et al. (2008) confirm that the explanatory power of order flows models is still much higher in the long run than the one of traditional exchange rate models.

Such results suggest that order flows provide an answer to the disconnection puzzle of the exchange rate. Indeed, order flows contain information about exchange rate fundamentals (Chinn and Moore (2008), Evans and Lyons (2005b, 2008), Rime, Sarno and Sojli (2010)). The only difference between order flows models and traditional models is that the information about exchange rate fundamentals contained in order flows has been processed by market agents. Conversely, traditional models only consider raw (or unprocessed) information about exchange rate fundamentals.

Processed information means information that has been treated by agents. Processed information contains the weight attributed by agents to the various types of information included in order flows: fundamental information (public and private), behavioural information (public and private) and information related to the trading mechanism of the foreign exchange market (the microstructure noise). Therefore order flow can be defined as a time-varying weight of fundamental information (public and private), behavioural information (public and private) and microstructure information. In comparison, traditional models only consider public fundamental information. Order flows $X_t$ can thus be defined as:

$$X_t = F_t(\Omega_t, B_t, M_t)$$

The term $\Omega_t$ represents the stock of information about macroeconomic fundamental considered by an agent at time $t$. This variable includes public information about macroeconomic fundamentals. The term $B_t$ stands for the behavioural noise affecting agents’
decisions. It includes the internal and external factors of market psychology. The term $M_t$ is the microstructure noise. It includes the noise relative to the trading mechanism peculiar to the foreign exchange market.

Therefore, the higher explanatory and predictive powers of order flows models compared to traditional models of exchange rate are justified by the fact that order flows contain processed or treated information while traditional models only consider raw information. In other words, beyond exchange rate fundamentals, order flows models consider the behavioural and microstructure components of exchange rates. Conversely, traditional models ignore such components and take only account of the fundamental information concerning exchange rates.

Given the importance of the behavioural and the microstructure components at short horizons relative to long horizons (Cheung and Wong (2000), Cheung and Chinn (2001), Cheung, Chinn and Marsh (2004))\(^{39}\), the explanatory power of order flows models is far better than the one of traditional exchange rate models in the short run. The difference in explanatory power between both models decreases in the long run (but is still in favour of order flows models (Berger et al. (2008))) because both the behavioural and the microstructure components play a minor role in the determination of the exchange at long run horizons (Cheung and Wong (2000), Cheung and Chinn (2001), Cheung, Chinn and Marsh (2004)).

6. Conclusion

This article aims at understanding the determinants of order flows in the foreign exchange rate market. We look inside the black box of order flows models to understand why order flows provide better explanatory and predictive powers of exchange rate dynamics than traditional models.

We set a theoretical model that takes account of all types of information available in the foreign exchange market. The model is based on two blocks. The first block is a behavioural exchange rate model based on heterogeneous agents (De Grauwe and Grimaldi (2007)) that provides the characteristics of customers faced by dealers. The second block is a microstructure model that represents the trading mechanism peculiar to the foreign exchange
market. The microstructure model is a simultaneous-trade model with a decentralised and multiple dealer structure.

Simulations from the model replicate important stylized facts observed empirically in the foreign exchange market.

First, the exchange rate is disconnected from its fundamentals in the short run but not from order flows. However, in the long run, the exchange rate returns towards its fundamental value and is close to order flows. Customer and interdealer order flows are highly correlated with exchange rate dynamics at all horizons. Besides the hot potato effect magnifies the amount of interdealer order flows relative to the amount of customer order flows.

Secondly, the model shows that the foreign exchange market is intrinsically inefficient. Indeed, information is distorted at two levels in the market. On the one hand, information is distorted by agents’ behaviours. This behavioural noise is split into two factors: internal factors and external factors. Internal factors include notably individual preferences, risk aversion, overreaction to news, specific models used by individuals. External factors cover rumours, mimetism and conventions. On the other hand, information is distorted by the trading mechanism peculiar to the foreign exchange market. This microstructure noise is caused by two factors brought by the hot potato effect: the noise relative to the interpretation of private information by dealers and the noise generated by the passing of undesired positions between dealers.

Thirdly, we argue that order flows models of exchange rate provide an answer to the exchange rate disconnection puzzle. Indeed, order flows models contain information that has been processed by market agents while traditional models only consider raw (or unprocessed) information. Thus, the information in order flows is a time-varying weight of fundamental information (both public and private), behavioural information (both public and private) and microstructure information. In comparison, traditional models only consider public fundamental information. The difference in the types of information considered by the two models explains why order flows models provide higher explanatory and predictive powers of exchange rate dynamics relative to traditional models.

\[39\text{ See appendix C.}\]
References


A. Definition of the different types of order flows

Three types of order flows can be found in the foreign exchange market. All three are related to the three main agents that operate in the foreign exchange market: brokers, market-makers and customers.

Brokers play the role of intermediaries in the foreign exchange market. Given a commission, their task is to match buyers and sellers among market-makers. Brokers are not allowed to take positions in the foreign exchange. Orders between market-makers and brokers are called brokered interdealer order flows. They are registered in electronic systems such as Reuters 3000 Spot Matching or EBS (Electronic Broking Service).

Market-makers negotiate the purchases and sells of currencies with their customers or with other market-makers directly or indirectly through brokers. Orders between market-makers are called direct interdealer order flows. They are registered in Reuters 3000 Dealing System. Usually big banks (such as Deutsche Bank, UBS, Barclays Capital, Citigroup, Royal Bank of Scotland, JP Morgan and HSBC) play the role of market-makers. Contrary to brokers, market-makers are allowed to take positions and thus speculate in the market. These positions are however limited. These limits are often set by risk managers given the degree of experience of traders and the degree of risk in the market. Market-makers must however close their positions by the end of the day. Market-makers often transfer their positions to customers or market-makers located in other time zones.

Eventually, customers operate in the foreign exchange market to convert currencies with a commercial or with a speculative objective. Customers are represented by non-financial companies (import-export firms, multinationals), institutional investors (pension funds, hedge funds) and sometimes central banks. Customers transmit their orders to market-makers. Such orders are called customer order flows and are registered in electronic systems of private banks.

An important characteristic of order flows is that order flow is private information. They are not released publicly and are only known by a minority of agents (usually market-makers). The most confidential orders are customer order flows followed by direct interdealer order flows and brokered interdealer order flows.
B. Description of the trading mechanism in the foreign exchange market

Order flow is a variable that provides a sign and an amount to a given transaction in the market. Buyers initiated order flows \((i.e.\) buy orders) are positively signed while sellers initiated order flows \((i.e.\) sell orders) are negatively signed. Net order flows is the difference between buy orders and sell orders on a given period of time. It is usual to consider net cumulated order flows to analyse the pressure on currency prices. Hence a positive net cumulated order flow is associated to an appreciation of a currency while a negative net cumulated order flow is associated to a depreciation of a currency.

According to Lyons (2001), order flow can be viewed as a mechanism that conveys private information into currency prices. Private information is information that is only known by a minority of agents in the market. We provide an example to illustrate the transmission of information in currency prices through order flows.

For sake of simplicity, we assume that every order has an aggressive part (Kyle (1985), Glosten and Milgrom (1985)) and ignore the existence of a limit order book. This assumption is relevant theoretically but not relevant empirically since empirically not all orders have an aggressive part and dealers do possess a limit order book.

**Figure B: The transmission of information in currency prices through order flows**

Suppose that the market is initially in equilibrium. Customer 1 analyses the fundamentals of the US dollar and finds that the dollar is over-appreciated against the euro. Customer 1 thus expects a depreciation of the dollar and decides to sell her stock of dollars...
against euro for 5 millions. Customer 1 hence gives a sell order of -5 to market-maker A. Market-maker A is observing the order flows transmitted by customer 1 and infers the information contained in the order flows. If the market-maker thinks that the customer sells her currency because of a worsening of macroeconomic fundamentals, he will then lower his listed price for the US dollar. Therefore, private information contained in customer 1’s order flows is thus introduced in the price of the currency. At this stage, cumulated order flows and net demand in the market are both equal to -5 (see table B).

Customer 2 is willing to buy 1 million dollars to market-maker A. The cumulated order flows and the net demand are both equal to -4. Market-maker A sells his whole stock of dollars to market-maker B. Market-maker B infers the negative information contained in the flows provided by market-maker A and decreases her price. Cumulated order flows decrease to -8 while net demand in the market remains unchanged at -4.

This mechanism will repeat itself for market-makers C, D and E. As market-makers take knowledge of the negative information contained in order flows, they decrease the price of the dollar in the market. Finally, the last transaction is materialised by an order of +2 from customer 4. Cumulated order flows amount to -12 while net demand is equal to zero. The market reaches a new equilibrium where customer 4 buys dollars at a new equilibrium price (i.e. at a lowered price).

Table B summarises the transactions that took place in the market.

<table>
<thead>
<tr>
<th>Transaction</th>
<th>Initial Part</th>
<th>Passive Part</th>
<th>Order Flow</th>
<th>Cumulated Order Flow</th>
<th>Customer cumulated net order flow</th>
<th>Net Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Customer 1</td>
<td>MM A</td>
<td>-5</td>
<td>-5</td>
<td>-5</td>
<td>-5</td>
</tr>
<tr>
<td>2</td>
<td>Customer 2</td>
<td>MM A</td>
<td>+1</td>
<td>-4</td>
<td>-4 (≡ -5 + 1)</td>
<td>-4</td>
</tr>
<tr>
<td>3</td>
<td>MM A</td>
<td>MM B</td>
<td>-4</td>
<td>-8</td>
<td>-4 (≡ -4 + 0)</td>
<td>-4</td>
</tr>
<tr>
<td>4</td>
<td>MM B</td>
<td>MM C</td>
<td>-4</td>
<td>-12</td>
<td>-4 (≡ -4 + 0)</td>
<td>-4</td>
</tr>
<tr>
<td>5</td>
<td>Client 3</td>
<td>MM C</td>
<td>+2</td>
<td>-10</td>
<td>-2 (≡ -4 + 2)</td>
<td>-2</td>
</tr>
<tr>
<td>6</td>
<td>MM C</td>
<td>MM D</td>
<td>-2</td>
<td>-12</td>
<td>-2 (≡ -2 + 0)</td>
<td>-2</td>
</tr>
<tr>
<td>7</td>
<td>MM D</td>
<td>MM E</td>
<td>-2</td>
<td>-14</td>
<td>-2 (≡ -2 + 0)</td>
<td>-2</td>
</tr>
<tr>
<td>8</td>
<td>Customer 4</td>
<td>MM E</td>
<td>+2</td>
<td>-12</td>
<td>0 (≡ -2 + 2)</td>
<td>0 (≡ -2 + 2)</td>
</tr>
</tbody>
</table>

Source: Marsh et O’Rourke (2005); MM stands for Market-Maker

Three observations can be highlighted from the above example.

First and along the lines of Lyons (2001), order flow is a mechanism that transmits private information into currency prices. Indeed private information about dollar’s fundamentals from customer 1 is spread in the market and included in currency prices through
order flows between market-makers. Once all the market-makers took knowledge of the negative information, the price of the currency reaches a new equilibrium.

Secondly, table B shows that net demand is strictly equal to cumulated customer order flows. This is due to the assumptions that every order has an aggressive part and also to the exclusion of a limit order book. Had we assume that all trades are not aggressive and also that dealers possess a limit order book, customer order flows would not have been strictly equal to the net demand. Customer order flows are the main source of information in the market. Information from customer order flows is then redistributed among market-makers. These redistributions of information take place through the transfers of unwanted positions of currencies by market-makers. Such redistributions explain the high volume of transactions between dealers in the foreign exchange market; the so-called hot potato effect. However, transactions between market-makers provide no additional information in the market relative to the original private information contained in customer order flows. Transactions between market-makers provide only transitory information through liquidity effects.

Thirdly, transactions between market-makers inflate the amount of flows in the market (as shown in the fifth column of table B related to cumulated order flows). Such flows magnify the effect of the initial order flows by customer 1. Hence if the price decreases as it was the case in the previous example, cumulated order flows decrease further more. In the above example, an initial customer order flow of -5 induces a final cumulated order flow of -12. Given the fact that the price has decreased between the first equilibrium and the second equilibrium, there appears a high correlation between the exchange rate and net cumulated order flows. This high correlation justifies the use of order flows as an explanatory variable for exchange rate dynamics.
C. The importance of investors’ behaviours at short run horizons

Beyond macroeconomic fundamentals, one of the major components of exchange rates in the short run is market psychology or equivalently agents’ behaviours (Keynes (1936), Hopper (1998)). The importance of this component has been justified by numerous surveys.

Cheung and Wong (2000) survey operators in the foreign exchange market in Tokyo, Hong Kong and Singapore between October 1995 and January 1996. They found that at intraday frequencies, exchange rates are exclusively driven by non-fundamental components (at 99.30 %): speculative forces (30.82 %), over-reaction (24.40 %) and bandwagon effects (24.40 %). In the medium run (shorter than 6 months) factors driving exchange rates are successively technical trading (39.75 %), economic fundamentals (32.14 %), speculative forces (14.0 %) and bandwagon effects (12.13 %). Hence, non-fundamental components still play a major role in explaining exchange rate dynamics (at 67.86 %). In the long run (longer than 6 months), operators consider that economic fundamentals are the main determinants of exchange rates (at 79.56 %).

Cheung and Chinn (2001) survey traders operating in the United States foreign exchange market between October 1996 and November 1997. At intraday frequencies, factors that best explain exchange rate dynamics are over-reaction (30.45 %), bandwagon effects (28.20 %) and speculative forces (25.51 %). Hence exchange rates are driven exclusively by non-fundamental components (at 98.56 %). In the medium run (up to 6 months) although economic fundamentals gain some importance (32.10 %), more than 66 % of respondents give credit to non-fundamental forces to explain exchange rate movements. Such non-fundamental forces include technical trading (30.52 %), speculative forces (23.68 %) and bandwagon effects (10.52 %). In the long run (over 6 months), operators consider that exchange rates are determined in majority by economic fundamentals (at 87.40 %).

Table C.1: Factors determining exchange rate movements (Cheung and Wong (2000))

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>24.40</td>
<td>12.13</td>
<td>0.84</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>30.16</td>
<td>1.98</td>
<td>0.20</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>30.82</td>
<td>14.0</td>
<td>2.30</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0.70</td>
<td>32.14</td>
<td>79.56</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>13.92</td>
<td>39.75</td>
<td>17.1</td>
</tr>
</tbody>
</table>

Source: Cheung and Wong (2000); Percentages of respondents in each category are mentioned.
Table C.2: Factors determining exchange rate movements (Cheung and Chinn (2001))

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>28,20</td>
<td>10,52</td>
<td>3,93</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>30,45</td>
<td>2,10</td>
<td>0</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>25,51</td>
<td>23,68</td>
<td>2,36</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0,82</td>
<td>32,10</td>
<td>87,40</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>14,40</td>
<td>30,52</td>
<td>3,14</td>
</tr>
<tr>
<td>Other</td>
<td>0,62</td>
<td>1,08</td>
<td>3,17</td>
</tr>
</tbody>
</table>

Source: Cheung and Chinn (2001); Percentages of respondents in each category are mentioned.

The same results can be found in Cheung, Chinn and Marsh (2004) who survey the United Kingdom foreign exchange market from March 1998 to April 1998. At intraday frequencies, non-fundamental forces determine exchange rates (at 97.7 %); mainly over-reaction to news (32.8 %), bandwagon effects (29.3 %) and speculative forces (25.3 %). In the medium run (within 6 months), non-fundamental forces play a major role in the determination of exchange rates (67.2 %) even if economic fundamentals gain importance (31.4 %). In the long run (over 6 months), economic fundamentals are the major determinants of exchange rates (at 82.5 %).

Table C.3: Factors affecting exchange rate dynamics (Cheung, Chinn and Marsh (2004))

<table>
<thead>
<tr>
<th>Factors</th>
<th>Intraday</th>
<th>Medium Run</th>
<th>Long Run</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwagon Effects</td>
<td>29,3</td>
<td>9,5</td>
<td>1</td>
</tr>
<tr>
<td>Over-Reaction to news</td>
<td>32,8</td>
<td>0,7</td>
<td>0</td>
</tr>
<tr>
<td>Speculative Forces</td>
<td>25,3</td>
<td>30,7</td>
<td>3,1</td>
</tr>
<tr>
<td>Economic Fundamentals</td>
<td>0,6</td>
<td>31,4</td>
<td>82,5</td>
</tr>
<tr>
<td>Technical Trading</td>
<td>10,3</td>
<td>26,3</td>
<td>11,3</td>
</tr>
<tr>
<td>Other</td>
<td>1,7</td>
<td>1,5</td>
<td>2,1</td>
</tr>
</tbody>
</table>

Source: Cheung, Chinn and Marsh (2004); Percentages of respondents in each category are mentioned.

D. Stationarity tests for series considered in the original model of Evans and Lyons (2001, 2002) (model (1) in the core text)

Stationarity tests are based on three tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Results are presented in tables D.1 and D.2.
Table D.1: Stationarity tests for endogenous variables $\Delta s_t$

<table>
<thead>
<tr>
<th>Currencies</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deutschemark</td>
<td>-8.84</td>
<td>-8.87</td>
<td>0.08***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td>Pound</td>
<td>-8.95</td>
<td>-8.98</td>
<td>0.03***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td>Yen</td>
<td>-9.45</td>
<td>-9.45</td>
<td>0.09***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
</tr>
</tbody>
</table>

NB: For the ADF test the Akaike criteria with 2 lags is considered; *p-values* are mentioned in brackets; stars denote a stationary series at a 1% (***, 5% (**), 10% (*) confidence level.

Table D.2: Stationarity tests for exogenous variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>$\Delta f(t_i - t_i^*)$</th>
<th>$\Delta X_t$</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Currencies</td>
<td>$\Delta s_t$</td>
<td>$\Delta s_t^*$</td>
<td>$\Delta s_t$</td>
<td>$\Delta s_t^*$</td>
<td>$\Delta s_t$</td>
<td>$\Delta s_t^*$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deutschemark</td>
<td>-8.72</td>
<td>-8.71</td>
<td>0.06***</td>
<td>-9.51</td>
<td>-9.50</td>
<td>0.07***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pound</td>
<td>-8.75</td>
<td>-8.75</td>
<td>0.10***</td>
<td>-6.89</td>
<td>-6.92</td>
<td>0.07***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yen</td>
<td>-7.91</td>
<td>-7.90</td>
<td>0.04***</td>
<td>-7.57</td>
<td>-7.60</td>
<td>0.18***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

NB: For the ADF test the Akaike criteria with 2 lags is considered; *p-values* are mentioned in brackets; stars denote a stationary series at a 1% (***, 5% (**), 10% (*) confidence level.

E. Stationarity tests for simulated series from the theoretical model

Stationarity tests are based on three tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Results are presented in table E.

Table E: Stationarity tests for the endogenous variable and exogenous variables simulated within the theoretical model of the foreign exchange market

<table>
<thead>
<tr>
<th>Variables</th>
<th>$s_t = F_t$</th>
<th>$\Delta f(t_i - t_i^*)$</th>
<th>$\Delta X_t$</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\overline{X} = (i_t - i_t^*)$</td>
<td>$V_2 = X_t$</td>
<td>$d\overline{X} = d(i_t - i_t^*)$</td>
<td>$dV_2 = dX_t$</td>
<td>$ds_t = dF_t$</td>
</tr>
<tr>
<td></td>
<td>-1.94</td>
<td>-3.69</td>
<td>-2.08</td>
<td>-6.10</td>
<td>-3.68</td>
<td>-9.06</td>
</tr>
<tr>
<td></td>
<td>(0.62)</td>
<td>(0.02)</td>
<td>(0.55)</td>
<td>(0.00)</td>
<td>(0.02)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>-2.39</td>
<td>-1.42</td>
<td>-2.65</td>
<td>-18.70</td>
<td>-2.53</td>
<td>-20.55</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(0.85)</td>
<td>(0.25)</td>
<td>(0.00)</td>
<td>(0.31)</td>
<td>(0.00)</td>
</tr>
<tr>
<td></td>
<td>1.27</td>
<td>0.34</td>
<td>1.27</td>
<td>0.04*</td>
<td>0.18***</td>
<td>0.04*</td>
</tr>
</tbody>
</table>

NB: For the ADF test the Akaike criteria with 2 lags is considered; *p-values* are mentioned in brackets; stars denote a stationary series at a 1% (***, 5% (**), 10% (*) confidence level.
F. Definition of the exogenous parameters used for simulations in the theoretical model of the foreign exchange market

Table F presents the parameters’ values set to run the simulations of the theoretical model of the foreign exchange rate market. The model was calibrated. The main sources for parameters’ values were De Grauwe and Grimaldi (2007) for the heterogeneous agents model and Lyons (1997) for the microstructure model.

<table>
<thead>
<tr>
<th>Agents</th>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Customers</strong></td>
<td><strong>Time t</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( n )</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>( \alpha_1 )</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>( \alpha_2 )</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>( \beta_1 )</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>( \beta_2 )</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>( \theta )</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>( \nu )</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>( \Lambda )</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>( \gamma )</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>( \mu )</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>( \delta )</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>( m )</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>( \mu_d )</td>
<td>2</td>
</tr>
<tr>
<td><strong>Dealers</strong></td>
<td><strong>Period 1</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Time t</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( \gamma_1 )</td>
<td>0.5 if ( OF_{\text{customer}} &lt; \bar{OF}<em>{\text{customer}} ); 1.5 if ( OF</em>{\text{customer}} &gt; \bar{OF}_{\text{customer}} )</td>
</tr>
<tr>
<td></td>
<td>( a_1 )</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>( a_2 )</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>( a_4 )</td>
<td>0.1</td>
</tr>
<tr>
<td><strong>Dealers</strong></td>
<td><strong>Period 2</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Time t</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>( \gamma_2 )</td>
<td>0.5 if ( T_{ij} &lt; \bar{T}<em>{ij} ); 1.5 if ( T</em>{ij} &gt; \bar{T}_{ij} )</td>
</tr>
<tr>
<td></td>
<td>( b_1 )</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>( b_2 )</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>( b_3 )</td>
<td>0.2</td>
</tr>
</tbody>
</table>
G. Precisions and remarks concerning the theoretical foreign exchange market model

In our model the price of the currency is affected through two channels: a direct channel and an indirect channel. The distinguishing feature between the two channels is easily understood with an example taken from Evans and Lyons (2008) and Evans (2009).

Assume a scheduled macroeconomic announcement on US gross domestic product (GDP) growth (i.e. common knowledge news) is greater than the expectations of market participants (other things being equal). Furthermore, suppose that all market agents agree that unexpectedly high US GDP growth represents good news for the dollar value. If all market agents agree that GDP growth is \( x \) percent higher than expected and, as a result, the dollar is \( y \) percent more valuable in terms of euro, then dealers will immediately quote a euro/dollar rate that is \( y \) percent higher. This is the standard mechanism - the direct channel - through which news directly impact on currency prices. Information that is common knowledge, i.e. public information, impacts currency prices through this direct channel.

Now assume that all market agents agree that the GDP announcement represents good news for the dollar, but that there are diverse opinions as to how large the appreciation should be. Under these circumstances, the initial rise in the euro/dollar spot rate could be viewed as too large by some market agents and too small by others. Those who view the rise as too small will place orders to purchase the dollar, while those who view the rise as too large will place orders to sell. In aggregate, the balance of these trades represents order flows that dealers use to further revise their spot rate quotes. In particular, positive (negative) order flows signal that the initial euro/dollar spot rate was below (above) the balance of opinion among market participants concerning the implications of the GDP announcement for the value of the dollar. This process of price adjustment via order flows is the indirect channel.\(^{40}\)

The indirect channel operates via order flows and conveys private information i.e. dispersed information about fundamentals to dealers. Dispersed information comprises micro-level information on economic activity that is correlated with fundamentals. Examples include the sales and orders for the products of individual firms, market research on consumer spending, and private research on the economy conducted by financial institutions, etc. Dispersed information first reaches the foreign exchange market via customer order flows received by individual dealers. These order flows have no immediate impact on dealers’ quotes because

\(^{40}\) Notice that good news for the dollar need not translate into positive order flows. Good news can be associated with either positive or negative order flows depending on how dealers’ initial adjusted quotes relate to the balance of opinion concerning the implications of the news.
they represent private information to the recipient dealer. The information in each customer flow will only impact on quotes once it is known to all dealers. Interdealer order flows are central to this process. Individual dealers use their private information to trade in the interdealer market. In so doing, information on their customer order flows is aggregated and spread across the market. Dispersed information is incorporated into dealers’ quotes once this information aggregation process is complete.
Abstract

This paper analyses empirically behaviours’ heterogeneity in the foreign exchange market and in stock markets. Results show that heterogeneous behaviours are homogenous across markets. However, the contagion of behaviours is significant between markets that trade the same asset but not significant between markets that trade different assets. We find that risk aversion explains behaviours’ heterogeneity contrary to macroeconomic fundamentals. When risk aversion is high (low), fundamentalists (chartists) dominate the market. Based on this stylised fact we build a behavioural forecasting rule. This rule provides better short and long run out-of-sample forecasts of future asset prices than the simple random walk.

Keywords: Exchange Rate, Stock Markets, Heterogeneous Agents, Markov Switching Model, Smoothing Threshold Autoregressive Model, Risk Aversion
Résumé

Ce papier analyse empiriquement l’hétérogénéité des comportements sur le marché de changes et sur les marchés boursiers. Les résultats montrent que les comportements hétérogènes sont homogènes entre marchés. Cependant, la contagion des comportements est significative entre marchés échangeant un même actif mais non significative entre marchés échangeant des actifs différents. Les résultats montrent que l’aversion au risque explique les comportements hétérogènes contrairement aux fondamentaux macroéconomiques. Ainsi lorsque l’aversion au risque est élevée (faible), les fondamentalistes (les chartistes) dominent le marché. Sur la base de ce fait stylisé, nous construisons une règle de prévision basée sur les comportements hétérogènes des agents. Cette règle fournit de meilleures prévisions en dehors de l’échantillon que le modèle de marche aléatoire à court terme comme à long terme.

Mots-Clés : Taux de Change, Marchés Boursiers, Agents Hétérogènes, Modèle à Changement de Régime Markovien, Modèle Autoregressif à Transition Lisse, Aversion au Risque
1. Introduction

The heterogeneous agents’ theory pioneered by Frankel and Froot (1986) provides an interesting mechanism to understand exchange rates dynamics. This mechanism is based on the observation that agents have heterogeneous expectations in the foreign exchange market. The main principle of these models is that the interactions between two (or more) agents with different behaviours (often chartists and fundamentalists) generate chaotic dynamics similar to the ones observed empirically for exchange rates. Empirical works pioneered by Vigfusson (1997) validate the theory of Frankel and Froot (1986).

De Grauwe and Grimaldi (2002, 2005a, 2005b, 2007) have recently revisited the work of Frankel and Froot (1986). Their innovations deal mainly with the introduction of elements from prospect theory (Kahneman and Tversky (1979)) and new criteria to choose a particular behavioural rule. Followers of De Grauwe and Grimaldi provide little extensions: some consider new behavioural rules (De Grauwe and Rovira Kaltwasser (2006, 2007), De Grauwe and Vansteenkiste (2007)) or new criteria for rules selection (De Grauwe and Markewicz (2006)); others add new markets (Picillo (2009)). The same observation holds concerning empirical models that follow the pioneered work of Vigfusson (1997). The theoretical and empirical literature on heterogeneous agents models remains focused under the light of the street lamp set respectively by Frankel and Froot (1987) and Vigfusson (1997). This article aims at highlighting new elements that might be located in the dark side of the street lamp.

We focus on the following questions. Which factors trigger empirically the trend reversal in exchange rates or equivalently which factors determine heterogeneous behaviours in financial markets? Is it risk aversion as put forward by De Grauwe and Grimaldi (2007) or is it the influence of macroeconomic fundamentals as early mentioned by Frankel and Froot (1986)? Besides, what can we tell about behaviours’ heterogeneity across different markets empirically? Do behaviours propagate across different markets or is there a common variable that triggers the same behaviours across financial markets?

To our best knowledge, the closest work to this article is Menkhoff, Rebitzky and Schröder (2009). Menkhoff et al. (2009) test the determinants of expectations’ heterogeneity in the foreign exchange market. They approximate expectations’ heterogeneity by computing expectations’ dispersion from a qualitative micro survey data of 300 practitioners with the Carlson and Parkin’s method (1975). To analyse the determinants of expectations’ heterogeneity, Menkhoff et al. (2009) rely on univariate and multivariate linear models. Our paper differs from the work of Menkhoff et al. (2009) in at least four points. First, our
analysis considers macro data and relies on two markets: the euro/dollar foreign exchange market and the European and US stock markets. Secondly, we compute expectations heterogeneity from the estimation of smoothed probabilities from a Markov-switching model. This non-linear model incorporates explicitly both the fundamentalist and the chartist rules. This framework allows us to test behaviours’ causality between various markets. Thirdly, we use non-linear TVTP Markov switching models and STAR models to test which variables are likely to determine heterogeneous behaviours in financial markets. Fourthly, we derive a forecasting rule based on our analysis of agents’ behaviours in financial markets.

We put forward three major results. Heterogeneous behaviours are homogenous across markets. Besides, the causality of behaviours is significant and strong within markets that trade the same asset (here between the European and US stock markets) but weaker or even not significant between two markets that trade different assets (here between either the European or the US stock markets, and the foreign exchange market). Secondly, we find that risk aversion (as proxied by implied volatility on option prices) is more likely to explain behaviours in financial markets than macroeconomic fundamentals. When risk aversion is higher than a critical value, fundamentalists dominate the market. Conversely, when risk aversion is lower than a critical value, the market is globally chartist. Thirdly, we build a behavioural forecasting rule based on this stylised fact. This rule provides better out-of-sample forecasts of future asset prices than the random walk. This observation stands in the long run as well as in the short run.

The remainder of the paper proceeds as follows. Section 2 presents a literature survey of theoretical and empirical works on behavioural exchange rate models. Section 3 estimates an heterogeneous agents model for the euro/dollar exchange rate and the European and US stock markets. We then analyse the interactions of behaviours between these markets. Section 4 tests which factors influence heterogeneous behaviours in financial markets based on TVTP Markov switching models and STAR models. Section 5 puts forward a forecasting rule based on agents’ behaviours. Section 6 concludes.
2. Literature survey

In a pioneered work, Frankel and Froot (1986) provide an interesting mechanism to understand exchange rate dynamics. This mechanism is based on the stylised fact that agents have heterogeneous behaviours in the foreign exchange market. Frankel and Froot represent behaviours’ heterogeneity by considering two agents: chartists and fundamentalists. Chartists interpolate past trends of exchange rates to forecast future exchange rate dynamics. Fundamentalists expect a return of the current exchange rate towards its fundamental value. The interactions between these two agents help to explain the dynamics of asset prices. When chartists dominate the market, the exchange rate wanders away from its fundamental value. Conversely, when fundamentalists dominate the market, the exchange rate returns towards its fundamental value.

Frankel and Froot use their model to explain the over-appreciation of the dollar in the mid-1980s. They show that between January 1980 and December 1982, the appreciation of the dollar with regards to major currencies of industrialised economies was justified by a real interest rate differential in favour of the United States. However between January 1983 and June 1985, Frankel and Froot relate the appreciation of the dollar to an “endogenous takeoff of a speculative bubble” since the dollar keeps appreciating although the real interest rate differential is no more in favour of the United States. Thus in that period, fundamentalist rules generate losses. Market agents have thus an incentive to switch to chartist rules. As the proportion of chartists increases in the market, the bubble inflates further and the exchange rate wanders away from its fundamental value. After July 1985, the dollar returns progressively towards its fundamental value. Frankel and Froot attribute this trend reversal in the dollar to the “ever-worsening current account deficit” in the United States. During the convergence of the dollar towards its fundamental value, the profitability of the fundamentalist rule increases leading to a rise in the proportion of fundamentalists in the market. The dollar reaches its fundamental value in December 1987 and the bubble disappears.

De Grauwe and Grimaldi (2002, 2005a, 2005b, 2007) have recently revisited the work of Frankel and Froot (1986). The innovations brought by De Grauwe and Grimaldi concern the introduction of psychological concepts such as the status quo bias, the long memory effects and elements from prospect theory (Kahneman and Tversky (1979)). Innovations have

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41 See table A, appendix A.
42 For more details, see appendix B.
also been brought on the criteria to choose a particular behavioural rule. However the underlying mechanisms of the model of De Grauwe and Grimaldi remain the same as in Frankel and Froot (1986). Theoretical models following De Grauwe and Grimaldi (2002, 2005a, 2005b, 2007) provide little extensions: some add new behavioural rules (De Grauwe and Rovira Kaltwasser (2006, 2007), De Grauwe and Vansteenkiiste (2007)) or new criteria for rules selection (De Grauwe and Markewicz (2006)); others add new markets (Picillo (2009)).

De Grauwe and Rovira Kaltwasser (2006) consider multiple agents that can choose between three forecasting rules: one fundamentalist rule and two chartist rules (a momentum rule and a simple extrapolative rule). Simulations of the model provide similar results as in De Grauwe and Grimaldi (2007). Exchange rate dynamics alternate between two regimes: a non-fundamental (bubble) regime in which the exchange rate wanders away from its fundamental value and a fundamental regime where the exchange rate fluctuates around its fundamental value. The determination of these regimes depends respectively on the increase and the decrease in the proportion of chartists in the market. Later, De Grauwe and Rovira Kaltwasser (2007) consider that agents can choose between three rules in the market: two fundamentalist rules (optimistic and pessimistic fundamentalists) and one chartist rule (a simple extrapolative rule). They find that the exchange rate alternates between three regimes: it wanders away from its fundamental value or fluctuates around it depending on the proportion of chartists and fundamentalists in the market and also according to the fundamentalist rule chosen by fundamentalists.

De Grauwe and Markewicz (2006) introduce new learning mechanisms in the selection of the rules (fitness learning and statistical learning). In fitness learning (similar to the one used in the model of De Grauwe and Grimaldi (2007)), weights attributed to a rule change according to the profitability of the rules (the parameters of the rules remain the same). In statistical learning, agents learn to improve these rules by revising the parameters in the behavioural rules (the weights attributed to a given rule remain the same). Under both learning mechanisms, simulations show that the exchange rate alternates between a bubble regime and a fundamental regime. De Grauwe and Markewicz (2006) show that fitness learning is more likely to reproduce the empirical puzzles of exchange rates (fundamental

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43 The theoretical model of De Grauwe and Grimaldi (2007) is exposed in appendix C.
44 De Grauwe and Altavilla (2010) present a similar model as in De Grauwe and Grimaldi (2007).
45 Prior to this study, De Grauwe and Vansteenkiiste (2007) proposed a model with two fundamentalist rules and one chartist rule. Fundamentalists have two divergent opinions about the value of the fundamental exchange rate while chartists rely on a momentum rule.
disconnection, excess volatility and volatility clustering) than statistical learning. Thus fitness learning is more likely to replicate agents’ behaviours in the foreign exchange market than statistical learning.

In a more innovative way, Piccillo (2009) regroups the approaches of De Gauwe and Grimaldi (2007) and Brock and Hommes (1998) by applying the heterogeneous agents model simultaneously to the stock market and to the foreign exchange market. Piccillo interestingly asks about the possible interactions of heterogeneous behaviours between both markets. Piccillo enriches the heterogeneous agents model by defining the fundamental value of the fundamentalist rules through a complete macroeconomic model based on a DSGE framework. Her model puts forward two theoretical results. First, when agents consider productivity shocks in only one of the markets, the dynamics of asset prices in the stock market and in the foreign exchange market is the same as the one described by De Gauwe and Grimaldi (2007). Indeed, in both markets, an increase in the chartists’ weight leads to a disconnection of asset prices from their fundamental value while an increase in the fundamentalists’ weight leads to a return of asset prices towards their fundamental value. Secondly, when agents consider productivity shocks coming from both the stock market and the foreign exchange market, the existence of a bubble in the stock market may create a bubble in the foreign exchange market (similar to the bubble created by chartists in the stock market) even if agents in the foreign exchange market are in majority fundamentalists. This interesting result is however not tested empirically. Her work remains essentially theoretical.


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46 Dynamic stochastic general equilibrium (DSGE) models attempt to explain aggregate economic phenomena such as economic growth, business cycles, and the effects of monetary and fiscal policies, on the basis of macroeconomic models derived from microeconomic principles. DSGE models aim to describe the behavior of the economy as a whole by analyzing the interaction of many microeconomic decisions. The decisions correspond to the determination of the amounts of consumption, saving, investment, labor supply and labor demand. The decision-makers may include households, business firms, governments or central banks. DSGE models are dynamic and study how the economy evolves over time. They are also stochastic, taking into account the fact that the economy is affected by random shocks such as technological change, fluctuations in the price of oil or errors in macroeconomic policy-making.

47 A detailed description of the model of Vigfusson (1997) is available in appendix D.
Studies following the original work of Vigfusson (1997) provide only minor extensions. Chan, Daw, Djoudad and Murray (2000) estimate the original model of Vigfusson (1997) for the exchange rates of Australia, Canada and New-Zealand against the United States between January 1973 and December 1999 in daily frequency. They consider three alternative chartist rules in their model (a momentum rule and a relative strength index (RSI) associated with a moving average convergence-divergence (MACD)). They found the same results as in Vigfusson (1997).

Ahrenz and Reitz (2003) rely on a similar model as in Vigfusson (1997) but assume constant volatility in both regimes ($\sigma_f=\sigma_c$). They estimate their model for the dollar/deutschemark exchange rate over the period January 1982-November 1998 on a daily frequency. Their results validate the hypotheses of Vigfusson (1997)’s model.

Bessec and Robineau (2003) test the robustness of Vigfusson’s results (1997). They consider four alternative models tested on the Canadian dollar, the deutschemark, the yen, against the US dollar between January 1983 and March 2000 in daily frequency. Their results validate the structure of the model used by Vigfusson (1997).

Other studies test the heterogeneous agents model by relying on threshold models rather than on Markov switching models.

Reitz and Westerhoff (2003) use a STAR model (Smooth Threshold Autoregressive model) to analyse the variation in the proportion of fundamentalists and chartists in the market according to the spread between the exchange rate and its fundamental value. They estimate their model for the deutschemark, the pound and the yen against the dollar between January 1980 and December 1996 in daily frequency. Their results show that when the exchange rate wanders away from its fundamental value, chartists dominate the market. A limit of their model is that there is no incentive for agents to become fundamentalist. In such circumstances, the inflation of a bubble is infinite.

Following Vigfusson (1997)’s results suggesting that chartists dominate in periods of low exchange rate volatility rather than in periods of high exchange rate volatility, Manzan and Westerhoff (2007) use a TAR model (Threshold Autoregressive model) to distinguish between two types of regimes for chartists. They consider respectively stabilising and destabilising chartists according to whether the exchange rate is more or less volatile. They estimate their model on the Canadian dollar, the French franc, the deutschemark, the British pound and the yen against the US dollar between January 1974 and December 1994 on a monthly frequency. Their results show that when exchange rate volatility is high, chartists

---

Murray, Van Norden and Vigfusson (1996) also expose the results related to the model of Vigfusson (1997).
favour a stabilising rule while when exchange rate volatility is low, chartists choose a destabilising rule. Their model provides however unsatisfying out-of-sample forecasts compared to the random walk.

More recently, Menkhoff *et al.* (2009) try to find the determinants of expectations heterogeneity in the foreign exchange market. They rely on a qualitative survey of monthly exchange rate expectations from about 300 forecasters that spans December 1991 to August 2006. Their sample covers three exchange rates: the US dollar, the British pound and the Japanese yen *vis-à-vis* the euro. They found that expectations dispersion is positively correlated with the decreasing deviation of the actual exchange rate from its fundamental value and also with abrupt changes in the exchange rate. Moreover, a rising exchange rate risk premium - as defined by the difference between the expected exchange rate and the accordant forward rate - increases expectations’ heterogeneity. Macroeconomic fundamentals (money, income, short term and long term interest rates, inflation, trade balance and capital flows) considered whether in absolute, in change or in variation do not affect significantly expectations’ dispersion.

Except the paper by Menkhoff *et al.* (2009), the literature survey shows that theoretical and empirical papers on heterogeneous agents remain focused on the same corner of the research field. Theoretical and empirical studies are mostly under the light of the street lamp set respectively by Frankel and Froot (1987) and Vigfusson (1997). Reasearchers do not go further in the lessons that can be drawn from heterogeneous agents models. They surprisingly stop at the variation of the proportion of chartists and fundamentalists in the market and its induced dynamics on the exchange rate. Perhaps, the studies of Piccillo (2009) and Menkhoff *et al.* (2009) open new ways of research in the literature concerning respectively theoretical and empirical models of heterogeneous agents.

The present article aims at highlighting new elements that might be located in the dark side of the street lamp. We start from the observation that in the Markov switching model of Vigfusson (1997), the state transition depends on an unobservable variable. Hence we still do not know which factors trigger empirically the trend reversal in exchange rates or equivalently which factors determine heterogeneous behaviours in the market? Is it risk aversion as put forward by De Grauwe and Grimaldi (2007) or is it the influence of macroeconomic fundamentals as early mentioned by Frankel and Froot (1986)? Besides, along with Piccillo (2009) what can we tell empirically about behaviours’ heterogeneity across different markets?
Do behaviours propagate across different markets or is there a common variable that triggers the same behaviour across financial markets? The present paper aims at answering these questions.

To our best knowledge, the closest paper to our analysis is Menkhoff et al. (2009). Our paper differs however strongly from Menkhoff et al. First of all, Menkhoff et al. consider qualitative micro data survey transformed into quantitative data by using the Carlson and Parkin (1975)’s method. Our paper considers quantitative macro data and uses smoothed probabilities computed from a quantitative model as a proxy for expectations’ heterogeneity. This quantitative model is based on a Markov switching framework and models explicitly the behaviours of fundamentalists and chartists in the market. The advantage of considering macro data relative to micro data is that macro data take account of the heterogeneous expectations of the market as a whole, contrary to micro survey data that consider only the heterogeneous expectations of the considered sample of surveyed practitioners. Secondly, Menkhoff et al. (2009) rely on purchasing power parity (PPP) to define the fundamental exchange rate. However the concept of PPP holds in the very long run. Besides, foreign exchange market surveys show that PPP becomes less popular among market agents as a fundamental definition for the exchange rate (Cheung and Chinn (2001)). Our paper uses a fundamental exchange rate estimated from a cointegration relationship based on macroeconomic fundamentals. Thirdly, Menkhoff et al. (2009) rely on univariate and multivariate OLS regressions. Such models are appropriate to find the determinants of expectations’ heterogeneity if one relies on micro data and does not specify explicitly the equations for fundamentalist and chartist behaviours. In our case, we rely on non-linear models (TVTP Markov switching models and STAR models) to test which variables are likely to determine heterogeneous behaviours in the foreign exchange market. Fourthly, our paper enriches the tests by Menkhoff et al. since it does not focus only on expectations’ heterogeneity in the foreign exchange market but considers also stock markets and the interaction of behaviours between both markets. Finally, we draw lessons from our analysis by deriving a forecasting rule from the analysis of agents’ behaviours in the markets.

Our research strategy is exposed as follows. In section 3 we analyse empirically agents’ heterogeneity in three markets: the foreign exchange market and the European and US stock markets. In section 4, we analyse the variables that trigger behaviours in financial markets among a set of financial and macroeconomic variables. Then, based on the lessons drawn from our analysis, section 5 defines a behavioural rule to forecast stock prices and exchange rates.
3. Analysis of the dynamics of heterogeneous agents in financial markets

3.1 Presentation of the models

We follow Vigfusson (1997) and test a traditional heterogeneous agents model based on a fixed transition probabilities (FTP) Markov switching framework. FTP Markov switching models - pioneered by Goldfeld and Quandt (1973) and applied to time series by Hamilton (1989) - assume that the transition between the state equations depends on an unobservable state variable that usually follows a Markov chain of order one. Assuming a FTP Markov switching model with two states - a chartist state and a fundamentalist state - the transition probabilities matrix is given by:

\[
\begin{bmatrix}
 P(S_t = c / S_{t-1} = c) & P(S_t = c / S_{t-1} = f) \\
 P(S_t = f / S_{t-1} = c) & P(S_t = f / S_{t-1} = f)
\end{bmatrix} = 
\begin{bmatrix}
 p & 1-q \\
 1-p & q
\end{bmatrix}
\]

For the euro/dollar exchange rate market, the heterogeneous agents model takes the following form:

\[
\Delta s_t = \begin{cases} 
\alpha_{11} + \alpha_{12}(\bar{s}_{t-1} - s_{t-1}) + \alpha_{13}(i_{t-1} - i^*_t) + \varepsilon_t^c & \text{if } S_t = f \\
\alpha_{21} + \alpha_{22}(ma_{t-1}^s - ma^s_{200,t-1}) + \alpha_{23}(i_{t-1} - i^*_t) + \varepsilon_t^f & \text{if } S_t = c
\end{cases}
\]  

(1)

With \(s_t\), the (log of the) exchange rate (the euro/dollar exchange rate is listed as 1 euro per \(S\) dollars); \(\bar{s}_t\), the (log of the) fundamental exchange rate; \(ma_{t-1}\), the moving average of the (log of the) exchange rate in the last \(\tau\) days\(^{49}\), \((i_{t-1} - i^*_t)\), the 10-years interest rate differential between the euro zone and the United States; \(\varepsilon_t^c \sim N(0, \sigma_c^2)\) and \(\varepsilon_t^f \sim N(0, \sigma_f^2)\); \(\alpha_{11}\) and \(\alpha_{21}\) are constants\(^{50}\). The fundamental exchange rate \(\bar{s}_t\) is defined as:

\[
\bar{s}_t = \bar{q}_t \cdot p_t + p_t^*
\]  

(2)

\(^{49}\) The \(\tau\) values considered here are the ones considered in Vigfusson (1997). The consideration of other figures for \(\tau\) does not alter the final results of the analysis. Results are available upon author request.

\(^{50}\) We consider macroeconomic fundamentals (i.e. the interest rate differential) in the Markov switching model because we assume agents are not purely chartist and fundamentalist. We assume agents take account of other information coming from fundamentals.
With $\overline{q}_t$, the (log of the) estimated real exchange rate; $p_t^*$, the (log of the) consumer price index in the United States; $p_t$, the (log of the) consumer price index in the Euro zone.

As the fundamental value of the price of an asset is a long term concept, we rely on an error correction model (ECM) to determine the fundamental value of the exchange rate\(^{51}\). Besides, because agents rely empirically on various fundamental models to determine the fundamental value of an asset, we consider three relationships:

- a UIP model (Keynes (1936)):

$$\overline{q}_t = \beta_0 + \beta_1 (r_t - r_t^*) + \epsilon_t$$  \hspace{1cm} (3a)

- a BEER model (Clark and MacDonald (1998)):

$$\overline{q}_t = \beta_0 + \beta_1 (r_t - r_t^*) + \beta_2 (a_t - a_t^*) + \beta_3 (e_d - e_d^*) + \epsilon_t$$  \hspace{1cm} (3b)

- a UIP-URP model\(^{52}\) (Heimonen and Vataja (2008)):

$$\overline{q}_t = \beta_0 + \beta_1 (r_t - r_t^*) + \beta_2 (sp_t - sp_t^*) + \beta_3 op_t + \epsilon_t$$  \hspace{1cm} (3c)

With \((a_t - a_t^*)\), the productivity differential; \((sp_t - sp_t^*)\), the stock price indices differential; \((e_d - e_d^*)\), the external debt differential; \(op_t\), the oil price index; \((r_t - r_t^*)\), the long-term real interest rate differential\(^{53}\).

For the European and US stock markets, the heterogeneous agents model takes the following form:

$$\Delta sp_t = \left\{ \begin{array}{ll}
\alpha_{11} + \alpha_{12} (sp_{t-1} - sp_{t-1}) + \alpha_{13} (i_{r-1} - i_{r-1}^u) + \epsilon_t & \text{if } S_t = f \\
\alpha_{21} + \alpha_{22} (ma_{14,t-1} - ma_{200,t-1}^u) + \alpha_{23} (i_{t-1} - i_{t-1}^u) + \epsilon_t^c & \text{if } S_t = c
\end{array} \right.\hspace{1cm} \text{(4)}$$

\(^{51}\) Fundamental models are estimated on a monthly frequency and not on a daily frequency because there is too much noise in the data at a daily frequency. See appendix F.

\(^{52}\) URP stands for uncovered equity return parity (Cappiello and De Santis (2005)). Appendix K provides elements to understand the concept of URP.

\(^{53}\) See appendix E for a detailed description of the series.
With $sp_t$, the (log of the) stock price index (respectively the Eurostoxx for the euro zone and the S&P500 for the United States); $\bar{sp}_t$, the (log of the) fundamental stock price index; $ma_{\tau+1}$, the moving average of the (log of the) stock price index in the period $\tau$; $(i^B_{\tau+1} - i^w_{\tau+1})$, the spread between the long term (10-years) interest rate and the short term (3-months) interest rate; $\varepsilon_t^c \rightarrow N(0, \sigma^c)$ and $\varepsilon_t^f \rightarrow N(0, \sigma^f)$; $\alpha_{11}$ and $\alpha_{21}$ are constant parameters.

The long-term value of the stock price index $\bar{sp}_t$ is based on the following long run relationship:\footnote{The fundamental model is estimated on a monthly frequency and not on a daily frequency because there is too much noise in the data at a daily frequency. See appendix H.}

$$\bar{sp}_t = \beta_0 + \beta_1^{spread} + \beta_2^{profit} + \beta_3 a_t + \beta_4 opt + \varepsilon_t$$  \hspace{1cm} (5)

With $\bar{sp}_t$, the (log of the) real stock price index; $spread_t$, the spread between the long term (10-years) real interest rate and the short term (3-months) real interest rate; $profit_t$, the (log of the) expected profits on the respective stock indices; $a_t$, the productivity of the economy; $opt_t$, the influence of oil prices on stock prices.\footnote{See appendix G for a detailed description of the series.}

As the fundamental value of the price of an asset is seen as a long term concept, we rely on an error correction model (ECM) to estimate the fundamental value of stock prices.

### 3.2 Output of the models

Models are estimated for the euro/dollar exchange rate, the Eurostoxx and the S&P500 between January 1990 and December 2009 on a daily frequency. The estimation procedure is based on the Maximum Likelihood (ML) algorithm and on the Expectation-Maximization (EM) algorithm (Dempster, Laird and Rubin (1977), Hamilton (1990)).\footnote{Models are run in GAUSS. A description of the EM algorithm is available in appendix I.}

For sake of robustness, we test various specifications of our models. We consider models with and without the interest rate differential ($nintd$) and also models with ARCH
components in the variance of the residuals\(^{57}\). Tables 1.1, 1.2 and 1.3 show the output of the estimations for each model.

Table 1.1: Output for the euro/dollar exchange rate

<table>
<thead>
<tr>
<th>Models</th>
<th>MLFTP ARCH</th>
<th>MLFTP ARCHnintd</th>
<th>MLFTP</th>
<th>MLFTP nintd</th>
<th>EMFTP</th>
<th>EMFTP nintd</th>
</tr>
</thead>
<tbody>
<tr>
<td>(S_t=f)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha_{11})</td>
<td>-0.30 [-0.74]</td>
<td>-1.68x10^{-4} [-3.10]</td>
<td>0.06x10^{-4} [0.06]</td>
<td>-0.21x10^{-3} [-0.74]</td>
<td>-0.36x10^{-3} [-0.81]</td>
<td>-0.21x10^{-3} [-0.74]</td>
</tr>
<tr>
<td>(\alpha_{12})</td>
<td>0.13x10^{-3} [0.45]</td>
<td>X</td>
<td>0.26x10^{-4} [2.91]</td>
<td>X</td>
<td>0.10x10^{-4} [0.30]</td>
<td>X</td>
</tr>
<tr>
<td>(\beta_{11})</td>
<td>8.99x10^{-3} [30.24]</td>
<td>0.08x10^{-3} [0.94]</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>(\beta_{12})</td>
<td>0.50 [0.80]</td>
<td>0.42 [4.02]</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>(S_t=c)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha_{21})</td>
<td>-0.65x10^{-4} [-0.70]</td>
<td>0.74x10^{-4} [0.39]</td>
<td>0.06x10^{-4} [0.17]</td>
<td>-0.02x10^{-4} [-0.02]</td>
<td>-0.03x10^{-4} [-0.02]</td>
<td>-0.02x10^{-4} [-0.02]</td>
</tr>
<tr>
<td>(\alpha_{22})</td>
<td>0.16x10^{-3} [1.86]</td>
<td>X</td>
<td>-0.34x10^{-4} [-1.31]</td>
<td>X</td>
<td>0.17x10^{-4} [1.98]</td>
<td>X</td>
</tr>
<tr>
<td>(\beta_{21})</td>
<td>5.06x10^{-3} [51.63]</td>
<td>0.02x10^{-3} [0.89]</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>(\beta_{22})</td>
<td>0.50 [0.33]</td>
<td>0.96 [2.07]</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Auto-correlation Tests</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(S_t=f)</td>
<td>48.17 (0.00)</td>
<td>21.85 (0.00)</td>
<td>2.79 (0.09)</td>
<td>18.72 (0.00)</td>
<td>2.11 (0.15)</td>
<td>2.26 (0.05)</td>
</tr>
<tr>
<td>(S_t=c)</td>
<td>38.51 (0.00)</td>
<td>12.65 (0.00)</td>
<td>2.78 (0.09)</td>
<td>8.35 (0.00)</td>
<td>13.61 (0.00)</td>
<td>47.25 (0.00)</td>
</tr>
<tr>
<td>(S_t=f,c)</td>
<td>10.63 (0.00)</td>
<td>21.73 (0.00)</td>
<td>2.79 (0.09)</td>
<td>14.98 (0.00)</td>
<td>13.65 (0.00)</td>
<td>57.41 (0.00)</td>
</tr>
<tr>
<td>Heteroskedasticity Tests</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(S_t=f)</td>
<td>2.63 (0.09)</td>
<td>2.16 (0.04)</td>
<td>22.88 (0.00)</td>
<td>25.26 (0.00)</td>
<td>23.38 (0.00)</td>
<td>1.11 (0.10)</td>
</tr>
<tr>
<td>(S_t=c)</td>
<td>0.9 (0.76)</td>
<td>0.12 (0.73)</td>
<td>23.29 (0.00)</td>
<td>29.61 (0.00)</td>
<td>121.34 (0.00)</td>
<td>32.54 (0.00)</td>
</tr>
<tr>
<td>(S_t=f,c)</td>
<td>1.31 (0.14)</td>
<td>2.17 (0.04)</td>
<td>24.24 (0.00)</td>
<td>47.07 (0.00)</td>
<td>129.47 (0.00)</td>
<td>47.27 (0.00)</td>
</tr>
<tr>
<td>Linearity Tests</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(S_t=f,c)</td>
<td>23.30 (0.00)</td>
<td>16.22 (0.00)</td>
<td>49.65 (0.00)</td>
<td>57.43 (0.00)</td>
<td>49.05 (0.00)</td>
<td>2.32 (0.67)</td>
</tr>
</tbody>
</table>

NB: FTP stands for fixed transition probabilities; nintd stands for no interest rate differential in the model. Student statistics are mentioned in square brackets; critical values for the test of Student amount to 1.96 at a 5 % confidence level and to 1.64 at a 10 % confidence level. Autocorrelation tests and heteroskedasticity tests follow a \(\chi^2\); linearity test follows a \(t\). The critical values for a \(\chi^2\) amount to 2.70 and 3.84 respectively at a 10 % and 5 % confidence level. The critical values for a \(t\) amount to 7.77 and 9.48 respectively at a 10 % and 5 % confidence level; \(p\)-values are mentioned in brackets.

Table 1.1 shows that fundamentalist rules have a positive and significant coefficient (this is not the case for the MLFTP model though). For the chartist rule, the coefficient is positive and significant (but not for the MLFTP and the MLFTPARCHnintd models). The

\(^{57}\) The coefficients \(\beta\) represent the coefficients of the ARCH component in the model, with respectively \(\sigma_{f,t}^2 = \beta_{11} + \beta_{12} e_{f,t-1}^2\), for \(S_t=f\); and \(\sigma_{c,t}^2 = \beta_{21} + \beta_{22} e_{c,t-1}^2\), for \(S_t=c\).
interest rate differential is only significant for the MLFTP model for the fundamentalist rule; and for the MLFTPARCH and EMFTP models in the chartist rule. Surprisingly, ARCH components (coefficients $\beta_{12}$ and $\beta_{22}$) appear not significant although we expect heteroskedasticity in the variance of residuals at such a high (daily) frequency.

Diagnostic tests show the presence of autocorrelation in the residuals. Besides, despite the ARCH correction, heteroskedasticity is still significant in the residuals. Also, linearity tests reject the hypothesis of the use of a non-linear Markov structure of order one for almost all models.

Table 1.2: Output for the European stock market

| Models | MLFTP ARCH | MLFTP ARCH|nintd | MLFTP | MLFTP | EMFTP | EMFTP |
|--------|------------|------------|-------|-------|-------|-------|
| $S_t=f$ | $\alpha_{11}$ | $-2.69 \times 10^{-3}$ | $[-3.91]$ | $-1.65 \times 10^{-3}$ | $[-2.93]$ | $0.76 \times 10^{-3}$ | $[-5.54]$ | $-1.91 \times 10^{-3}$ | $[-3.09]$ | $-2.84 \times 10^{-3}$ | $[-3.76]$ | $-1.91 \times 10^{-3}$ | $[-2.99]$ |
|         | $\alpha_{12}$ | $3.52 \times 10^{-3}$ | $[1.63]$ | $5.76 \times 10^{-3}$ | $[3.03]$ | $2.43 \times 10^{-3}$ | $[2.19]$ | $4.99 \times 10^{-3}$ | $[2.34]$ | $3.13 \times 10^{-3}$ | $[1.34]$ | $4.99 \times 10^{-3}$ | $[1.99]$ |
|         | $\alpha_{13}$ | $1.32 \times 10^{-3}$ | $[2.74]$ | $X$ | $0.05 \times 10^{-4}$ | $[0.06]$ | $1.27 \times 10^{-3}$ | $[2.48]$ | $X$ |
|         | $\beta_{11}$ | $0.30 \times 10^{-3}$ | $[0.92]$ | $0.30 \times 10^{-3}$ | $[0.94]$ | $X$ | $X$ | $X$ | $X$ |
|         | $\beta_{12}$ | $0.49$ | $[0.53]$ | $0.91$ | $[1.69]$ | $X$ | $X$ | $X$ | $X$ |
| $S_t=c$ | $\alpha_{21}$ | $0.64 \times 10^{-3}$ | $[4.16]$ | $0.64 \times 10^{-3}$ | $[4.17]$ | $-3.08 \times 10^{-3}$ | $[-3.80]$ | $0.62 \times 10^{-3}$ | $[4.40]$ | $0.63 \times 10^{-3}$ | $[4.18]$ | $0.62 \times 10^{-3}$ | $[4.23]$ |
|         | $\alpha_{22}$ | $2.35 \times 10^{-3}$ | $[1.01]$ | $2.51 \times 10^{-3}$ | $[1.07]$ | $-3.99 \times 10^{-3}$ | $[-1.25]$ | $2.43 \times 10^{-3}$ | $[1.24]$ | $2.28 \times 10^{-3}$ | $[1.09]$ | $2.43 \times 10^{-3}$ | $[1.08]$ |
|         | $\alpha_{23}$ | $0.03 \times 10^{-4}$ | $[0.03]$ | $X$ | $1.66 \times 10^{-3}$ | $[3.27]$ | $X$ | $0.06 \times 10^{-4}$ | $[0.06]$ | $X$ |
|         | $\beta_{21}$ | $0.04 \times 10^{-3}$ | $[0.82]$ | $0.04 \times 10^{-3}$ | $[0.81]$ | $X$ | $X$ | $X$ | $X$ |
|         | $\beta_{22}$ | $0.50$ | $[93.41]$ | $0.02 \times 10^{-4}$ | $[0.00]$ | $X$ | $X$ | $X$ | $X$ |

Auto-correlation Tests

<table>
<thead>
<tr>
<th>$S_t=f$</th>
<th>21.90</th>
<th>28.04</th>
<th>9.66</th>
<th>8.48</th>
<th>1.26</th>
<th>49.30</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_t=c$</td>
<td>13.73</td>
<td>29.07</td>
<td>4.26</td>
<td>9.55</td>
<td>19.21</td>
<td>16.35</td>
</tr>
<tr>
<td>$S_t=f,c$</td>
<td>25.57</td>
<td>8.35</td>
<td>10.63</td>
<td>35.91</td>
<td>15.96</td>
<td>21.47</td>
</tr>
</tbody>
</table>

Heteroskedasticity Tests

<table>
<thead>
<tr>
<th>$S_t=f$</th>
<th>4.85</th>
<th>4.91</th>
<th>42.00</th>
<th>118.09</th>
<th>3.82</th>
<th>4.38</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_t=c$</td>
<td>0.26</td>
<td>1.53</td>
<td>135.05</td>
<td>38.65</td>
<td>0.00</td>
<td>20.47</td>
</tr>
<tr>
<td>$S_t=f,c$</td>
<td>5.97</td>
<td>4.91</td>
<td>138.21</td>
<td>120.20</td>
<td>3.47</td>
<td>24.84</td>
</tr>
</tbody>
</table>

Linearity Tests

| $S_t=f,c$ | 10.30 | 22.33 | 123.94 | 126.46 | 36.94 | 0.13 |

NB: FTP stands for fixed transition probabilities; nintd stands for no interest rate differential in the model. Student statistics are mentioned in square brackets; critical values for the test of Student amount to 1.96 at a 5% confidence level and to 1.64 at a 10% confidence level. Autocorrelation tests and heteroskedasticity tests follow a $\chi^2(1)$; linearity test follows a $\chi^2(4)$. The critical values for a $\chi^2(1)$ amount to 2.70 and 3.84 respectively at a 10% and 5% confidence level. The critical values for a $\chi^2(4)$ amount to 7.77 and 9.48 respectively at a 10% and 5% confidence level; $p$-values are mentioned in brackets.

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For the European stock market, fundamentalist rules have a positive and significant coefficient. This coefficient is however not significant in the EMFTP model. The coefficients associated to the chartist rules appear unsignificant. The spread between the long run and the short run interest rates is only significant for the MLFTP model. Moreover, the coefficients associated to ARCH components (coefficients $\beta_{12}$ and $\beta_{22}$) are significant only for the MLFTPARCH model.

Diagnostic tests show the presence of autocorrelation and heteroskedasticity in the residuals for the majority of models despite the ARCH correction. Linearity tests reject the hypothesis of the use of a non-linear Markov structure of order one for almost all models.

### Table 1.3: Output for the US stock market

<table>
<thead>
<tr>
<th>Models</th>
<th>MLFTP ARCH</th>
<th>MLFTP ARCH/niind</th>
<th>MLFTP</th>
<th>MLFTP niind</th>
<th>EMFTP</th>
<th>EMFTP niind</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{t}=f$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{11}$</td>
<td>-0.41x10^{-3} [4,74]</td>
<td>0.57x10^{-3} [77]</td>
<td>0.57x10^{-3} [77]</td>
<td>0.96x10^{-3} [79]</td>
<td>-0.63x10^{-3} [-1,38]</td>
<td></td>
</tr>
<tr>
<td>$\alpha_{12}$</td>
<td>5.78x10^{-3} [2,01]</td>
<td>2.14x10^{-3} [2,00]</td>
<td>2.14x10^{-3} [2,00]</td>
<td>7.06x10^{-3} [1,80]</td>
<td>3.50x10^{-3} [1,53]</td>
<td></td>
</tr>
<tr>
<td>$\alpha_{13}$</td>
<td>0.71x10^{-3} [1,21]</td>
<td>1.20x10^{-3} [0,30]</td>
<td>-0.95x10^{-3} [-1,43]</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_{11}$</td>
<td>0.35x10^{-3} [4,74]</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>$\beta_{12}$</td>
<td>0.50 [3,00]</td>
<td>0.93 [3,00]</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>$S_{t}=c$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{21}$</td>
<td>0.65x10^{-3} [3,76]</td>
<td>0.74x10^{-3} [6,39]</td>
<td>-0.76x10^{-3} [-1,55]</td>
<td>-0.74x10^{-3} [-1,50]</td>
<td>0.95x10^{-3} [3,43]</td>
<td>0.62x10^{-3} [3,85]</td>
</tr>
<tr>
<td>$\alpha_{22}$</td>
<td>-1.05x10^{-3} [-0,38]</td>
<td>0.20x10^{-3} [0,07]</td>
<td>-2.63x10^{-3} [-0,61]</td>
<td>-2.77x10^{-3} [-0,68]</td>
<td>-0.88x10^{-3} [-0,25]</td>
<td>-0.04x10^{-3} [-0,17]</td>
</tr>
<tr>
<td>$\alpha_{23}$</td>
<td>0.71x10^{-3} [1,21]</td>
<td>0.34x10^{-3} [-0,71]</td>
<td>X</td>
<td>0.16x10^{-3} [-1,65]</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>$\beta_{21}$</td>
<td>0.50 [0,69]</td>
<td>0.40x10^{-3} [0,69]</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>$\beta_{22}$</td>
<td>0.50 [0,73]</td>
<td>0.71 [2,20]</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

**Auto-correlation Tests**

| $S_{t}=f$ | 8.00 (0,00) | 12.13 (0,00) | 7.72 (0,00) | 5.65 (0,01) | 5.84 (0,02) | 5.65 (0,01) |
| $S_{t}=c$ | 9.86 (0,00) | 4.10 (0,04) | 6.08 (0,01) | 11.84 (0,00) | 0.58 (0,10) | 11.84 (0,00) |
| $S_{t}=f,c$ | 13.79 (0,00) | 5.34 (0,02) | 7.43 (0,00) | 30.29 (0,00) | 1.61 (0,20) | 30.29 (0,00) |

**Heteroskedasticity Tests**

| $S_{t}=f$ | 2.72 (0,09) | 1.91 (0,02) | 7.19 (0,00) | 7.08 (0,00) | 11.49 (0,00) | 7.08 (0,00) |
| $S_{t}=c$ | 0.44 (0,50) | 0.12 (0,73) | 36.56 (0,00) | 36.77 (0,00) | 36.77 (0,00) | 36.77 (0,00) |
| $S_{t}=f,c$ | 3.90 (0,04) | 19.14 (0,00) | 72.68 (0,00) | 8.88 (0,00) | 8.88 (0,00) | 8.88 (0,00) |

**Linearity Tests**

| $S_{t}=f,c$ | 35.13 (0,00) | 35.04 (0,00) | 54.63 (0,00) | 55.07 (0,00) | 51.41 (0,00) | 54.98 (0,00) |

NB: See NB of table 1.2.
Table 1.3 shows that the coefficients associated to the fundamentalist rule are positive and significant (unsignificant for the EMFTPrintd model though). The coefficients associated to the chartist rule appear unsignificant for every model; as are the coefficients related to the spread between the long run and the short run interest rates. Once again, ARCH components (coefficients $\beta_{12}$ and $\beta_{22}$) appear not significant.

Diagnostic tests show the presence of autocorrelation in the residuals. Besides, despite the ARCH correction, heteroskedasticity is significant in the residuals. Linearity tests reject the hypothesis of the use of a non-linear Markov structure of order one for every model.

Globally, fundamentalist rules appear significant in the majority of the models. Therefore, when the price of the asset wanders away from its fundamental value, agents expect a return of the price of the asset towards its fundamental value. Conversely, the coefficients associated to the chartist rules appear in majority unsignificant. This result is difficult to justify given the fact that we consider a daily frequency and for such a high frequency, momentum effects are highly important in the dynamics of asset prices. Coefficients associated to the interest rate differential and to the spread between the long run and the short run interest rates appear in majority unsignificant. This result is again difficult to justify because both variables play an important role in the determination of respectively, the exchange rate and stock prices. Besides, for every model, diagnostic tests show a strong presence of autocorrelation and heteroskedasticity. Also, linearity tests reject the hypothesis of the use of a non-linear Markov structure of order one for every model. This result is often observed in studies using a Markov switching structure of order one (Vigfusson (1997), Bessec and Robineau (2003)). The literature suggests considering more than two states.
Table 2: Conditional probabilities, unconditional probabilities and regime duration

<table>
<thead>
<tr>
<th>Models</th>
<th>MLFTP ARCH</th>
<th>MLFTP ARCH\text{hintd}</th>
<th>MLFTP</th>
<th>EMFTP</th>
<th>EMFTP \text{hintd}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euro/Dollar</td>
<td>(\sigma_1) 9.00 \times 10^{-5}</td>
<td>1.78 \times 10^{-5}</td>
<td>4.987 \times 10^{-5}</td>
<td>5.022 \times 10^{-5}</td>
<td>0.82 \times 10^{-5}</td>
</tr>
<tr>
<td></td>
<td>(\sigma_c) 5.10 \times 10^{-5}</td>
<td>6.90 \times 10^{-5}</td>
<td>4.977 \times 10^{-5}</td>
<td>4.987 \times 10^{-5}</td>
<td>0.25 \times 10^{-5}</td>
</tr>
<tr>
<td></td>
<td>(p) 0.89</td>
<td>0.91</td>
<td>0.86</td>
<td>0.90</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>(q) 0.84</td>
<td>0.86</td>
<td>0.91</td>
<td>0.85</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>(p_{\text{ln}}) 0.59</td>
<td>0.61</td>
<td>0.39</td>
<td>0.60</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>(q_{\text{ln}}) 0.41</td>
<td>0.39</td>
<td>0.61</td>
<td>0.40</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>(d_f) 9</td>
<td>11</td>
<td>7</td>
<td>10</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>(d_c) 6</td>
<td>7</td>
<td>11</td>
<td>7</td>
<td>25</td>
</tr>
</tbody>
</table>

| Euro/S	ext{Stoxx} | \(\sigma_1\) 1.74 \times 10^{-5} | 1.69 \times 10^{-5} | 5.017 \times 10^{-5} | 5.047 \times 10^{-5} | 0.36 \times 10^{-5} | 0.36 \times 10^{-5} |
|                    | \(\sigma_c\) 7.00 \times 10^{-5} | 6.90 \times 10^{-5} | 5.047 \times 10^{-5} | 5.017 \times 10^{-5} | 0.05 \times 10^{-5} | 0.05 \times 10^{-5} |
|                    | \(p\) 0.91 | 0.91 | 0.86 | 0.91 | 0.98 | 0.98 |
|                    | \(q\) 0.86 | 0.86 | 0.91 | 0.86 | 0.96 | 0.96 |
|                    | \(p_{\text{ln}}\) 0.61 | 0.61 | 0.39 | 0.61 | 0.66 | 0.66 |
|                    | \(q_{\text{ln}}\) 0.39 | 0.39 | 0.61 | 0.39 | 0.34 | 0.34 |
|                    | \(d_f\) 11 | 11 | 7 | 11 | 50 | 50 |
|                    | \(d_c\) 7 | 7 | 11 | 7 | 25 | 25 |

| S&P 500          | \(\sigma_1\) 1.61 \times 10^{-5} | 1.78 \times 10^{-5} | 5.017 \times 10^{-5} | 5.017 \times 10^{-5} | 0.32 \times 10^{-5} | 0.32 \times 10^{-5} |
|                  | \(\sigma_c\) 6.80 \times 10^{-5} | 6.90 \times 10^{-5} | 5.054 \times 10^{-5} | 5.054 \times 10^{-5} | 0.04 \times 10^{-5} | 0.04 \times 10^{-5} |
|                  | \(p\) 0.90 | 0.91 | 0.87 | 0.87 | 0.98 | 0.98 |
|                  | \(q\) 0.88 | 0.86 | 0.90 | 0.90 | 0.97 | 0.97 |
|                  | \(p_{\text{ln}}\) 0.55 | 0.61 | 0.43 | 0.43 | 0.60 | 0.60 |
|                  | \(q_{\text{ln}}\) 0.45 | 0.39 | 0.57 | 0.57 | 0.40 | 0.40 |
|                  | \(d_f\) 10 | 11 | 8 | 8 | 50 | 50 |
|                  | \(d_c\) 8 | 7 | 10 | 10 | 34 | 34 |

NB: Conditional probabilities \(p = P(S_t=f|S_{t-1}=c), q = P(S_t=c|S_{t-1}=f)\); Unconditional probabilities: \(\pi_f = (1-q)/(2-p-q), \pi_c = (1-p)/(2-p-q)\); Regime expected duration (in days): \(d_f = 1/(1-p), d_c = 1/(1-q)\).

Table 2 shows that for a majority of models, state variances are higher in the fundamentalist regime than in the chartist regime. Thus fundamentalists dominate the market in periods of high asset price volatility while chartists dominate in periods of low asset price volatility. This result is often found in the literature (Murray \textit{et al.} (1996), Vigfusson (1997) and Bessec and Robineau (2003)).

For a majority of models, conditional probabilities show that when agents are chartist in the past, there is a high probability that they will be fundamentalist in the future (\(p > q\)). As a matter of facts, results based on the EM algorithm show that the probabilities to be in the fundamentalist state amount to 0.66 or 0.60 while the probabilities to be in the chartist state amount to 0.34 or 0.40 (\(\pi_f > \pi_c\)).

Also, in the majority of cases, the duration of the fundamentalist regime lasts almost twice as much as the duration of the chartist regime (\(d_f > d_c\)). Therefore, markets alternate between a long-lasting regime characterised by high volatility - the fundamentalist regime - and a short-lasting regime characterised by low volatility - the chartist regime.
We have estimated here our heterogeneous agents models based on two algorithms: the ML algorithm and the EM algorithm. However, our estimations show that the EM algorithm provides more stable and more robust results than the ML algorithm. Particularly, with the ML algorithm, the final estimated parameters are highly dependent on the choice of the initial parameters contrary to the EM algorithm. As a result, we choose to carry on the analysis based on the results from the most robust and most general of our models: the EMFTP model\(^{58}\).

3.3 Graphical analysis

The following graphs represent the smoothed probabilities of being in the fundamentalist regime. These probabilities are estimated from the EMFTP model. The blue margins \((P(S_t=f/I_T)>0.5)\) indicate that the market is in majority fundamentalist while the white margins \((P(S_t=f/I_T)<0.5)\) indicate that the market is in majority chartist.

\(^{58}\) Other reasons lead us to carry on the analysis with the results based on the EM algorithm. First, the time of convergence of the algorithm is lower with the EM algorithm than with the ML algorithm. Secondly, a lot of studies rely on the EM algorithm to estimate the models considered here (Vigfusson (1996), Bessec and Robineau (2003) among others).
For every market, smoothed probabilities confirm the dynamics exposed earlier in the theoretical model of Frankel and Froot (1986) and De Grauwe and Grimaldi (2007). When chartists dominate the market, the exchange rate wanders away from its fundamental value.
When the spread between the actual exchange rate and the fundamental exchange rate increases and reaches a given level, fundamentalists become dominant in the market. The increase in the weight of fundamentalists leads the exchange rate towards its fundamental value. For the euro/dollar exchange rate, trend reversals appear for example between December 2000 and April 2001 and also between August 2008 and June 2009.


Further, the homogeneity of behaviours across markets increases all over the period. For example, at the beginning of the period, shocks affecting only the foreign exchange market (the EMS crisis in 1992-1993) or only the stock market (the stock crash of 1990) did not generate homogeneous behaviours in the three markets, contrary to shocks at the end of the period (the internet bubble and the subprime crisis). We justify this observation by the increasing financial integration between the three markets over the considered period. This increasing homogeneity in market behaviours increases the instability of financial markets in periods of financial turmoil.

We go further into the analysis. We try to understand whether this continuous degree of integration between the foreign exchange market and stock markets can be observed by homogeneity effects at the level of agents’ behaviours in the foreign exchange market and in stock markets.

Table 3 shows the results of Granger causality tests on heterogeneous behaviours in the euro/dollar market, the European stock market and the US stock market between January 1990 and December 2009. We assume that behaviours’ heterogeneity can be proxied by smoothed probabilities computed from the EMFTP model.
Table 3: Granger causality tests between behaviours (smoothed probabilities) on the euro/dollar exchange rate, the Eurostoxx and the S&P500

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>Behaviours</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P500 does not Granger cause Eurostoxx</td>
<td>23.46 (0.00)</td>
</tr>
<tr>
<td>Eurostoxx does not Granger cause S&amp;P500</td>
<td>8.15 (0.00)</td>
</tr>
<tr>
<td>S&amp;P500 does not Granger cause the euro/dollar exchange rate</td>
<td>0.08 (0.91)</td>
</tr>
<tr>
<td>The euro/dollar exchange rate does not Granger cause S&amp;P500</td>
<td>1.01 (0.36)</td>
</tr>
<tr>
<td>Eurostoxx does not Granger cause the euro/dollar exchange rate</td>
<td>4.42 (0.01)</td>
</tr>
<tr>
<td>The euro/dollar exchange rate does not Granger cause Eurostoxx</td>
<td>0.20 (0.81)</td>
</tr>
</tbody>
</table>

NB: Ganger tests were carried out in EViews 6; 2 lags (two days) are considered in the second column; 21 lags (1 month) are considered in the third column; *p*-values are mentioned in brackets.

Table 3 shows a significant bi-causality between behaviours in the European and the US stock markets. The causality is weaker between stock markets and the foreign exchange market. We notice however a significant unilateral causality from behaviours on the European stock market towards behaviours on the euro/dollar market. The causality is not significant between behaviours on the US stock market and behaviours on the euro/dollar market.

Therefore the contagion of agents’ behaviours is significant and strong within markets that trade the same asset (here between the European and US stock markets) but weaker or even not significant between two markets that trade different assets (here between either the European or the US stock markets, and the foreign exchange market).

Besides, agents’ behaviours in the three markets are similar. Thus, heterogeneous behaviours are homogeneous across markets\(^\text{59}\). Given the fact that heterogeneous behaviours are homogeneous across financial markets and also that the causality of agents’ behaviours is strongly significant between markets that trade the same asset but weaker between markets that trade different assets, one may wonder which factor drives the simultaneity in market agents’ behaviours? The following section aims at providing answers.

\(^{59}\) Our empirical results do not validate the theoretical results of Picillo (2009). Picillo finds that there could be chartist domination in one market and fundamentalist domination in a second market. The existence of a bubble triggered by chartists in the first market may create a bubble in the second market (similar to the bubble created by chartists in the first market) although agents in the second market are in majority fundamentalists. Here the models show on the one hand that behaviours tend to be similar across markets; and on the other hand, that the causality between behaviours on the foreign exchange market and behaviours on stock markets is weak or even
4. Which variable(s) trigger(s) heterogeneous behaviours in financial markets?

4.1 Motivation of the analysis

This section aims at analysing which variable(s) drive(s) the intervention of chartists and fundamentalists in stock markets and in the foreign exchange market? The theoretical literature about heterogeneous agents considers that two types of shocks can trigger a particular behaviour in the foreign exchange market. The first types of shocks are exogenous shocks such as the intervention of public authorities or unexpected shocks in macroeconomic fundamentals (Frankel and Froot (1986)). The second types of shocks are endogenous shocks; caused for example by the variation of the spread between the actual value of the exchange rate and its fundamental value. Endogenous shocks can also be illustrated by a variation in the degree of risk aversion in the market (De Grauwe and Grimaldi (2007)).

The method used to unveil the variables that determine agents’ behaviours in financial markets are based on time-varying transition probabilities (TVTP) Markov switching models and on smooth transition autoregressive (STAR) models.

4.1.1 Markov switching models with time-varying transition probabilities

TVTP Markov Switching models were pioneered by the work of Diebold et al. (1994), Engel and Hakkio (1994) and Filardo (1994). Contrary to FTP models, TVTP Markov switching models assume that the transitions between state equations depend on an observable state variable $z$. Thus the transition probabilities are allowed to vary over time depending on the value of the observable variable $z$. Assuming a TVTP Markov switching model with two states (a chartist state and a fundamentalist state), the transition probabilities matrix is given by:

\[
\begin{bmatrix}
P(S_i = c / S_{i-1} = c) & P(S_i = c / S_{i-1} = f) \\
P(S_i = f / S_{i-1} = c) & P(S_i = f / S_{i-1} = f)
\end{bmatrix} =
\begin{bmatrix}
p(z_{i-1}) & 1 - q(z_{i-1}) \\
1 - p(z_{i-1}) & q(z_{i-1})
\end{bmatrix}
\]

not significant. Thus when chartists dominate in the foreign exchange market, there is a high probability that chartists also dominate in stock markets and vice versa.
The transition probabilities are modelled as a logistic functional form such as:

\[
\begin{bmatrix}
P(S_t = c / S_{t-1} = c, z_{t-1}; \beta_0) & P(S_t = c / S_{t-1} = f, z_{t-1}; \beta_1) \\
P(S_t = f / S_{t-1} = c, z_{t-1}; \beta_0) & P(S_t = f / S_{t-1} = f, z_{t-1}; \beta_1)
\end{bmatrix} = \begin{bmatrix}
\frac{\exp(z_{t-1}' \beta_0)}{1 + \exp(z_{t-1}' \beta_0)} & 1 - \frac{\exp(z_{t-1}' \beta_1)}{1 + \exp(z_{t-1}' \beta_1)} \\
\frac{\exp(z_{t-1}' \beta_0)}{1 + \exp(z_{t-1}' \beta_0)} & \frac{\exp(z_{t-1}' \beta_1)}{1 + \exp(z_{t-1}' \beta_1)}
\end{bmatrix}
\]

For the euro/dollar exchange rate market, the heterogeneous agents model takes the following form:

\[
\Delta s_t = \begin{cases}
\alpha_{11} + \alpha_{12}(\delta_{t-1} - s_{t-1}) + \varepsilon_t^f & \text{if } S_t = f \\
\alpha_{21} + \alpha_{22}(ma_{14,t-1} - ma_{200,t-1}) + \varepsilon_t^c & \text{if } S_t = c
\end{cases}
\] (6)

For the European and US stock markets, we define the heterogeneous agents model as:

\[
\Delta s_p_t = \begin{cases}
\alpha_{11} + \alpha_{12}(\delta_{p,t-1} - s_{p,t-1}) + \varepsilon_t^f & \text{if } S_t = f \\
\alpha_{21} + \alpha_{22}(ma_{14,t-1} - ma_{200,t-1}) + \varepsilon_t^c & \text{if } S_t = c
\end{cases}
\] (7)

Notice that we do not consider macroeconomic fundamentals anymore (i.e. interest rate differentials and spreads between the long run and the short run interest rates) in the TVTP Markov switching models. Indeed, we fear macroeconomic factors would bias the choice of the threshold variable (notably, when we test whether interest rates - a macroeconomic fundamental - is a significant determinant of heterogeneous behaviours).

The TVTP Markov switching model is estimated by relying on the Maximum Likelihood approach⁶⁰.

---

⁶⁰ Models are run in GAUSS.
4.1.2 Smooth threshold autoregressive models

In order to determine if agents’ behaviour depends on the dynamics of a particular variable, we rely also on STAR models (Smooth Transition Autoregressive models). In STAR models the state transitions depend on an observable variable often called the threshold variable. The advantage of STAR models with regards to TVTP Markov switching models is that STAR models allow estimating a threshold value $\lambda$ for the threshold variable.

For the euro/dollar exchange rate market, the STAR model takes the following form:\(^\text{61}\):

$$\Delta s_t = \begin{cases} 
\alpha_{11} + \alpha_{12} (\bar{s}_{t-1} - s_{t-1}) + \epsilon_i^f & \text{if } z_{t-1} > \lambda \\
\alpha_{21} + \alpha_{22} (m_{14,t-1}^s - m_{200,t-1}^s) + \epsilon_i^e & \text{if } z_{t-1} \leq \lambda
\end{cases} \quad (8)$$

For the European and US stock markets, we define the model as:

$$\Delta sp_t = \begin{cases} 
\alpha_{11} + \alpha_{12} (\bar{sp}_{t-1} - sp_{t-1}) + \epsilon_i^f & \text{if } z_{t-1} > \lambda \\
\alpha_{21} + \alpha_{22} (m_{14,t-1}^{sp} - m_{200,t-1}^{sp}) + \epsilon_i^e & \text{if } z_{t-1} \leq \lambda
\end{cases} \quad (9)$$

Thus, if the threshold variable $z_{t-1}$ is higher than the critical value $\lambda$, then the endogenous variable $\Delta s_t$ is determined in majority by the fundamentalist rule. Conversely, if the threshold variable $z_{t-1}$ is lower or equal to the critical value $\lambda$, then the endogenous variable $\Delta s_t$ is determined in majority by the chartist rule.

STAR models assume that the transition between the states is smooth. This smooth transition is allowed by introducing a continuous transition function $F(z_{t-1}; \gamma, \lambda)$ bounded between 0 and 1. We can thus express (8) as:

$$\Delta s_t = \left[\alpha_{11} + \alpha_{12} (\bar{s}_{t-1} - s_{t-1})\right][1 - F(z_{t-1}; \gamma, \lambda)] + \left[\alpha_{21} + \alpha_{22} (m_{14,t-1}^s - m_{200,t-1}^s)\right]F(z_{t-1}; \gamma, \lambda) + \epsilon_i \quad (10)$$

\(^\text{61}\) Once again, we do not consider macroeconomic fundamentals in behavioural rules of the STAR model for the same reasons as the ones mentioned for the TVTP Markov switching model.
Where $\lambda$ is the threshold parameter; $\gamma$ measures the transition speed between regimes. Two types of transition functions will be considered in this analysis: the logistic function which defines the logistic STAR ($LSTAR$) model (equation (11)); and the exponential function that defines the exponential STAR ($ESTAR$) model (equation (12))$^{62}$:

\[
F(z_{t-1}; \gamma, \lambda) = \frac{1}{1 + \exp[-\gamma(z_{t-1} - \lambda)]} \tag{11}
\]

\[
F(z_{t-1}; \gamma, \lambda) = 1 - \exp[-\gamma(z_{t-1} - \lambda)^2] \tag{12}
\]

The STAR model is estimated according to the Maximum Likelihood estimation technique performed through the standard Newton-Raphson algorithm$^{63}$.

4.2 Estimation of the models and discussion of the results

Both the TVTP Markov switching models and the STAR models are estimated on the euro/dollar exchange rate, the Eurostoxx and the S&P500 between January 1990 and December 2009 on a daily frequency.

We consider two types of indicators as determinants of agents’ heterogeneous behaviours. We first consider macroeconomic indicators: the absolute weekly variation in the short run (3 months) interest rate for stock markets and the foreign exchange market, the daily absolute variation in the dividend yield for stock markets, the quarterly absolute variation in the current account/GDP (Frankel and Froot (1986)) for the foreign exchange market. Secondly, we consider market sentiment indicators: the risk aversion (in level) as approximated by the implied volatility computed on at-the-money option prices$^{64}$ (De Grauwe and Grimaldi (2007)) and the monthly variation in consumer and entrepreneurs confidence indices for both the stock markets and the foreign exchange market. The choice of such fundamentals is justified by the fact that such variables are considered in the theoretical

$^{62}$ We rely on the logistic and the exponential functions because such functions are often used in the literature that aims at modelling exchange rate dynamics (see for example, Kilian and Taylor (2003), Reitz and Westerhoff (2003)).

$^{63}$ Models are run in SAS.

$^{64}$ Implied volatility on option prices is often used by practitioners to assess the degree of risk aversion in the market. For example, the Chicago Board Options Exchange (CBOE) has created in 1993 the implied volatility on the S&P500 options; also known as the VIX. The VIX is considered by practitioners as the fear index (or fear gauge) of investors in the US stock market. For more details about implied volatility and risk aversion, see appendix L.
models of heterogeneous agents (Frankel and Froot (1986), De Grauwe and Grimaldi (2007)) and/or in the recent study by Menkhoff et al. (2009).

Estimation results concerning macroeconomic fundamentals and confidence indices used as determinant variables of heterogeneous behaviours appear unrobust\textsuperscript{65}. These results are in line with Menkhoff et al. (2009). We therefore conclude that there is no evidence of a robust relationship between macroeconomic fundamentals and the heterogeneity of agents’ behaviours. On the contrary, results concerning risk aversion used as a determinant variable of heterogeneous behaviours appear more robust. We thus focus on these latest results. Table 4 shows the output of the TVTP Markov switching models and STAR models, with risk aversion considered as a determinant of agents’ behaviours.

\textsuperscript{65} Results based on macroeconomic fundamentals are highly unstable and thus not robust either for TVTP Markov switching models or for STAR models. Such results are rather surprising because at first sight graphical analyses show that the probability to be in the fundamentalist regime coincides with large movements in macroeconomic fundamentals. However no significant influence by macroeconomic fundamentals in the
Table 4: Output for risk aversion as an explanatory variable of heterogeneous behaviours in financial markets

<table>
<thead>
<tr>
<th>TVTP Markov switching models</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficients</td>
<td>Euro/Dollar</td>
<td>Eurostoxx</td>
</tr>
<tr>
<td>$S_t=f$</td>
<td>$\alpha_{11}$</td>
<td>$-0.12 \times 10^{-3}$</td>
<td>$1.17 \times 10^{-3}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[-0.29]$</td>
<td>$[5.63]$</td>
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<tr>
<td></td>
<td>$\alpha_{12}$</td>
<td>$8.63 \times 10^{-3}$</td>
<td>$6.68 \times 10^{-3}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[2.18]$</td>
<td>$[4.68]$</td>
</tr>
<tr>
<td>$S_t=c$</td>
<td>$\alpha_{21}$</td>
<td>$-0.12 \times 10^{-3}$</td>
<td>$-2.68 \times 10^{-3}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[-0.92]$</td>
<td>$[-2.62]$</td>
</tr>
<tr>
<td></td>
<td>$\alpha_{22}$</td>
<td>$10.28 \times 10^{-3}$</td>
<td>$-2.46 \times 10^{-3}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[3.21]$</td>
<td>$[-0.03]$</td>
</tr>
<tr>
<td>Transition Parameter</td>
<td>$z$</td>
<td></td>
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</tr>
<tr>
<td></td>
<td></td>
<td>$9.57$</td>
<td>$64.77$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[1.66]$</td>
<td>$[1.92]$</td>
</tr>
<tr>
<td>Linearity Test</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$22.37$</td>
<td>$124.18$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
</tr>
<tr>
<td></td>
<td>Exponential STAR models</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coefficients</td>
<td>Euro/Dollar</td>
<td>Eurostoxx</td>
</tr>
<tr>
<td>$S_t=f$</td>
<td>$\alpha_{11}$</td>
<td>$-1.11$</td>
<td>$-12.55$</td>
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<tr>
<td></td>
<td></td>
<td>$[-0.11]$</td>
<td>$[-8.69]$</td>
</tr>
<tr>
<td></td>
<td>$\alpha_{12}$</td>
<td>$0.36$</td>
<td>$2.93$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[0.07]$</td>
<td>$[0.17]$</td>
</tr>
<tr>
<td>$S_t=c$</td>
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<td>$-0.67 \times 10^{-3}$</td>
<td>$-0.01$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[-0.50]$</td>
<td>$[-0.96]$</td>
</tr>
<tr>
<td></td>
<td>$\alpha_{22}$</td>
<td>$-0.03$</td>
<td>$-0.23$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[-0.12]$</td>
<td>$[-3.91]$</td>
</tr>
<tr>
<td>Threshold Parameter</td>
<td>$\lambda$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>$0.09$</td>
<td>$0.75$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[3.11]$</td>
<td>$[453.00]$</td>
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<tr>
<td>Linearity Test</td>
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</tr>
<tr>
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<td></td>
<td>$7.04$</td>
<td>$9.71$</td>
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<td>$(0.00)$</td>
<td>$(0.00)$</td>
</tr>
<tr>
<td></td>
<td>Logistic STAR models</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>Coefficients</td>
<td>Euro/Dollar</td>
<td>Eurostoxx</td>
</tr>
<tr>
<td>$S_t=f$</td>
<td>$\alpha_{11}$</td>
<td>$4.93$</td>
<td>$0.23$</td>
</tr>
<tr>
<td></td>
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<td>$[0.10]$</td>
<td>$[8.20]$</td>
</tr>
<tr>
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<td>$\alpha_{12}$</td>
<td>$-9.99$</td>
<td>$1.05$</td>
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<tr>
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<td>$[-0.10]$</td>
<td>$[3.86]$</td>
</tr>
<tr>
<td>$S_t=c$</td>
<td>$\alpha_{21}$</td>
<td>$-7.03 \times 10^{-3}$</td>
<td>$16.66$</td>
</tr>
<tr>
<td></td>
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<td>$[-0.52]$</td>
<td>$[1.33]$</td>
</tr>
<tr>
<td></td>
<td>$\alpha_{22}$</td>
<td>$-0.03$</td>
<td>$-26.19$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[-0.12]$</td>
<td>$[-1.33]$</td>
</tr>
<tr>
<td>Threshold Parameter</td>
<td>$\lambda$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td>$0.04$</td>
<td>$0.30$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$[61.32]$</td>
<td>$[13.57]$</td>
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<tr>
<td>Linearity Test</td>
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</tr>
<tr>
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<td>$5.03$</td>
<td>$10.47$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$(0.00)$</td>
<td>$(0.00)$</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; $p$-values are mentioned in brackets. For the Eurostoxx, and the euro/dollar exchange rate, the test for risk aversion is run from January 1999 to December 2009 due to data availability.

Table 4 shows that the coefficients associated to the transition variable $z$ are significant for the TVTP Markov switching models. Also, the threshold value $\lambda$ is significant for the STAR models. Therefore, both the TVTP Markov switching models and the STAR
determination of agents’ behaviours is found based on either TVTP Markov switching models or STAR models. Results are available upon author request.
models show that risk aversion is a significant determinant of agents’ behaviours in financial markets.

Concerning diagnostic tests, we observe that the hypothesis of a non-linear model is rejected for every specification. We also notice that LSTAR models provide more robust results than ESTAR models. Indeed, ESTAR models often provide excessive values for the Student statistics.

Besides, the output of STAR models is more easily interpretable from an economic perspective than the one of TVTP Markov switching models.

As mentioned previously, STAR models show that the threshold value $\lambda$ is highly significant for all markets. There is thus a non-linear structure in the dynamics of asset prices that can be modelled with the degree of risk aversion as a threshold variable. Results tell us that if risk aversion increases in the market above a given threshold, fundamentalists dominate the market. Conversely, when risk aversion decreases under a given threshold, the market becomes chartist. We end up with the same results as the one mentioned in section 3.3: fundamentalists dominate in times of crisis (when risk aversion increases) while chartists dominate in times of boom (when risk aversion decreases). From a behavioural perspective, these results mean that agents are more rational in times of crisis (since they rely more on fundamentals to forecast asset prices) than in times of boom (where agents rely more on chartist analysis and ignore fundamentals).

One of the main advantages of STAR models compared to TVTP Markov switching models is to provide an objective estimation of the threshold value. We thus carry on the analysis by considering the threshold values estimated from STAR models since these threshold values act as a reference point to determine which type of behaviours prevail in the market.

Figures 2.1 to 2.3 show the dynamics of asset prices, the probability to be in the fundamentalist regime estimated from the Markov switching model (section 3) and the degree of risk aversion for the three markets.
In line with the results from STAR models, figure 2.1 shows a strong relationship between the implied volatility on the S&P500 and the intervention of fundamentalists in the market. Indeed, each time the implied volatility becomes higher than 25, fundamentalists dominate the market. Conversely, below 25, chartists dominate the market.

The same observation holds for the Eurostoxx and the euro/dollar exchange rate (figures 2.2 and 2.3). When implied volatility is higher (lower) than 0.35, fundamentalists (chartists) dominate in the European stock market. When implied volatility is higher (lower) than 0.12 in the euro/dollar foreign exchange market, fundamentalists (chartists) dominate in the euro/dollar foreign exchange market.

It is worth to notice that the threshold values highlighted graphically (in figures 2.1, 2.2 and 2.3) are close to the ones estimated by the LSTAR model in table 4.
As a result, the theoretical intuition of De Grauwe and Grimaldi (2007) based on prospect theory\(^{66}\) seems to be validated. De Grauwe and Grimaldi endogenise the trend reversal based on a stylised fact observed in agents’ behaviours: the more agents realise losses, the more they are willing to take risks. This stylised fact has been highlighted by Kahneman and Tversky (1979) in the prospect theory. De Grauwe and Grimaldi (2007) state that when exchange rates move away from their fundamental value, fundamentalists realise losses. Such losses lower the risk aversion of fundamentalists and lead them to use their rule more often. The increase in the use of fundamentalist rules makes in turn the use of fundamentalist rules more profitable. The induced increase in the proportion of fundamentalists in the market then triggers the return of the exchange rate towards its fundamental value.

However, our tests do not strictly verify the statements of De Grauwe and Grimaldi (2007) since we do not distinguish between fundamentalist risk aversion and chartist risk aversion. We only rely on a global measure of risk aversion for the whole market.

\(^{66}\) See appendix B.
5. Assessing the forecasting power of a behavioural forecasting rule

The analysis of heterogeneous behaviours in the foreign exchange market and in stock markets has highlighted a stylised fact. When risk aversion increases and is high in the market, fundamentalists dominate. Conversely, when risk aversion decreases and becomes low, chartists dominate the market. This section aims at building a forecasting rule based on this stylised fact. Due to the relatively high degree of parameter instability within the Markov switching and STAR frameworks, we decided not to rely on these models to compute our forecasts. Rather we will use more stable models. We describe our forecasting strategy below.

For each market, we consider three models: a fundamentalist rule, a chartist rule and a definition of the fundamental value of the asset.

First of all, we estimate in-sample the fundamental value of the asset from January 1990 to December 2002. The fundamental models ((13a) and (13b)) are estimated by $OLS$. We then forecast the fundamental value out-of-sample between January 2003 and December 2009. We use recursive forecasts\(^{67}\).

\[
\overline{sP}_{t+k} = \beta_0 + \beta_1 \text{spread}_t + \beta_2 \text{profit}_t + \beta_3 a_t + \beta_4 \text{op}_t + \varepsilon_{t+k} \tag{13a}
\]

\[
\overline{q}_{t+k} = \beta_0 + \beta_1 (r_t - r_t^*) + \beta_2 (a_t - a_t^*) + \beta_3 (ed_t - ed_t^*) + (sp_t - sp_t^*) + \beta_5 \text{op}_t + \varepsilon_{t+k} \tag{13b}
\]

\(^{67}\)Recursive forecasts aim at estimating the model in-sample for a given period of time and forecasting the endogenous variable out-of-sample. We then estimate the model by adding one observation to the previous in-sample period (the initial date of the in-sample period remains the same). We iterate this procedure until the end of the sample period.
Our forecasting rule is based on the analysis of heterogeneous behaviours in the markets. We observe risk aversion at time $t$ (as proxied by the implied volatility on option prices). If risk aversion $\alpha$ is higher than the critical value $\lambda$, then forecasts are based on the fundamentalist rule$^{68}$. Conversely, if risk aversion $\alpha$ at time $t$ is lower than the critical value $\lambda$, we rely on the chartist rule to forecast future asset prices. We thus have:

\[
\Delta s_{t+k} = \begin{cases} 
\alpha_{11} + \alpha_{12} (\pi_{t+k} - s_t) + \varepsilon_{t+k} & \text{if } \alpha_t > \lambda \\
\alpha_{21} + \alpha_{22} (ma_{14,t} - ma_{200,t}) + \varepsilon_{t+k} & \text{if } \alpha_t < \lambda 
\end{cases}
\]

\[
\Delta p_{t+k} = \begin{cases} 
\alpha_{11} + \alpha_{12} (\pi_{t+k} - s_t) + \varepsilon_{t+k} & \text{if } \alpha_t > \lambda \\
\alpha_{21} + \alpha_{22} (ma_{14,t} - ma_{200,t}) + \varepsilon_{t+k} & \text{if } \alpha_t < \lambda 
\end{cases}
\]

Where $\pi_{t+k} = \pi_{t+k} - p_t + p^*_t$ \hspace{1cm} (13c)

Based on our previous analysis, we assume $\lambda = 25$ for the S&P500, $\lambda = 0.35$ for the Eurostoxx and $\lambda = 0.12$ for the euro/dollar exchange rate. Behavioural rules (13c) are estimated in-sample from January 1990 to December 2002 on a daily frequency. We rely on a GARCH model estimated by Maximum Likelihood. We then forecast our models out-of-sample from January 2003 to December 2009. Again we use recursive forecasts.

We compare the forecasts from our behavioural forecasting rule to the ones from a random walk without drift:

\[
s_{t+k}^{RW} = s_t + \varepsilon_{t+k} \quad \text{Where } \varepsilon_{t+k} \rightarrow iidN(0, \sigma^2) \hspace{1cm} (13d)
\]

Tables 5.1 to 5.3 show the forecast errors of the random walk and the behavioural forecasting rule for short and long run horizons i.e. horizons spanning from 1 day to 5 years$^{69}$.

---

$^{68}$ Note that we include the forecasted fundamental series ($\pi_{t+k}$) from equations (13a) and (13b) in the fundamental rules of each respective market.

$^{69}$ Forecasts series are computed in Eviews and MATLAB.
Table 5.1: Out-of-sample forecasts of the behavioural forecasting rule for the euro/dollar exchange rate

<table>
<thead>
<tr>
<th>Horizon (in days)</th>
<th>RMSE</th>
<th>RMSE RW</th>
<th>U-Theil</th>
<th>MAE</th>
<th>MAE RW</th>
<th>U-Theil</th>
<th>%DirCh</th>
<th>%DirCh RW</th>
<th>U-Theil</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.01</td>
<td>0.01</td>
<td>0.99 (0.00)</td>
<td>0.01</td>
<td>0.01</td>
<td>0.99 (0.23)</td>
<td>48.28</td>
<td>50.57</td>
<td>0.95 (0.68)</td>
</tr>
<tr>
<td>5</td>
<td>0.02</td>
<td>0.02</td>
<td>1.00 (0.00)</td>
<td>0.00</td>
<td>0.01</td>
<td>0.02 (0.12)</td>
<td>44.83</td>
<td>45.98</td>
<td>0.97 (0.82)</td>
</tr>
<tr>
<td>10</td>
<td>0.02</td>
<td>0.02</td>
<td>0.99 (0.00)</td>
<td>0.00</td>
<td>0.02</td>
<td>0.11 (0.95)</td>
<td>54.02</td>
<td>54.02</td>
<td>1.00 (1.00)</td>
</tr>
<tr>
<td>21</td>
<td>0.04</td>
<td>0.04</td>
<td>0.99 (0.00)</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04 (0.57)</td>
<td>51.72</td>
<td>52.87</td>
<td>0.97 (0.77)</td>
</tr>
<tr>
<td>63</td>
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<td>0.07</td>
<td>0.97 (0.00)</td>
<td>0.00</td>
<td>0.05</td>
<td>0.09 (0.19)</td>
<td>51.76</td>
<td>52.94</td>
<td>0.97 (0.77)</td>
</tr>
<tr>
<td>126</td>
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<td>0.10</td>
<td>0.96 (0.00)</td>
<td>0.01</td>
<td>0.08</td>
<td>0.11 (0.01)</td>
<td>52.44</td>
<td>52.44</td>
<td>1.00 (1.00)</td>
</tr>
<tr>
<td>252</td>
<td>0.13</td>
<td>0.13</td>
<td>0.94 (0.00)</td>
<td>0.02</td>
<td>0.12</td>
<td>0.13 (0.00)</td>
<td>50.00</td>
<td>50.00</td>
<td>1.00 (1.00)</td>
</tr>
<tr>
<td>504</td>
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<td>0.15</td>
<td>0.79 (0.00)</td>
<td>0.05</td>
<td>0.11</td>
<td>0.40 (0.02)</td>
<td>50.00</td>
<td>51.56</td>
<td>0.96 (1.00)</td>
</tr>
<tr>
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<td>0.17</td>
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<td>0.92 (0.48)</td>
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<td>0.19</td>
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<td>0.70 (0.00)</td>
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<td>0.24</td>
<td>0.59 (0.33)</td>
<td>53.57</td>
<td>50.00</td>
<td>1.07 (0.51)</td>
</tr>
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</table>

NB: RMSE (RMSE RW) stands for Root Mean Square Errors of the behavioural forecasting rule (respectively the random walk); MAE (MAE RW) stands for Mean Absolute Errors of the behavioural forecasting rule (respectively the random walk); %DirCh (%DirCh RW) stands for the average percentage of right direction in the forecasts of future prices of the behavioural forecasting rule (respectively the random walk); U-Theil = Statinvestmentrule/StatRW; p-values associated to the Diebold-Mariano (1995) statistics are mentioned in brackets.

Table 5.2: Out-of-sample forecasts of the behavioural forecasting rule for the Eurostoxx

<table>
<thead>
<tr>
<th>Horizon (in days)</th>
<th>RMSE</th>
<th>RMSE RW</th>
<th>U-Theil</th>
<th>MAE</th>
<th>MAE RW</th>
<th>U-Theil</th>
<th>%DirCh</th>
<th>%DirCh RW</th>
<th>U-Theil</th>
</tr>
</thead>
<tbody>
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<td>3.04</td>
<td>1.00 (0.00)</td>
<td>2.23</td>
<td>2.23</td>
<td>0.99 (0.93)</td>
<td>56.32</td>
<td>54.02</td>
<td>1.04 (0.67)</td>
</tr>
<tr>
<td>5</td>
<td>6.99</td>
<td>7.01</td>
<td>0.99 (0.00)</td>
<td>0.17</td>
<td>5.39</td>
<td>0.03 (0.00)</td>
<td>49.43</td>
<td>50.57</td>
<td>0.97 (0.81)</td>
</tr>
<tr>
<td>10</td>
<td>9.59</td>
<td>9.76</td>
<td>0.98 (0.00)</td>
<td>0.46</td>
<td>7.35</td>
<td>0.06 (0.00)</td>
<td>45.98</td>
<td>44.83</td>
<td>1.02 (0.82)</td>
</tr>
<tr>
<td>21</td>
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<td>15.44</td>
<td>1.00 (0.00)</td>
<td>1.87</td>
<td>11.57</td>
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<td>60.92</td>
<td>1.00 (1.00)</td>
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<td>29.38</td>
<td>1.01 (0.01)</td>
<td>5.35</td>
<td>22.79</td>
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<td>1.00 (1.00)</td>
</tr>
<tr>
<td>126</td>
<td>49.37</td>
<td>47.70</td>
<td>1.03 (0.02)</td>
<td>10.76</td>
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<td>0.28 (0.00)</td>
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<td>59.76</td>
<td>1.02 (0.79)</td>
</tr>
<tr>
<td>252</td>
<td>86.03</td>
<td>79.63</td>
<td>1.08 (0.01)</td>
<td>26.86</td>
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<td>0.40 (0.00)</td>
<td>61.33</td>
<td>59.21</td>
<td>1.17 (0.04)</td>
</tr>
<tr>
<td>504</td>
<td>134.44</td>
<td>121.76</td>
<td>1.10 (0.01)</td>
<td>49.79</td>
<td>109.12</td>
<td>0.45 (0.00)</td>
<td>56.25</td>
<td>57.81</td>
<td>0.97 (0.77)</td>
</tr>
<tr>
<td>756</td>
<td>138.90</td>
<td>132.16</td>
<td>1.05 (0.00)</td>
<td>44.61</td>
<td>124.83</td>
<td>0.35 (0.00)</td>
<td>55.77</td>
<td>57.69</td>
<td>0.96 (0.76)</td>
</tr>
<tr>
<td>1260</td>
<td>119.37</td>
<td>105.60</td>
<td>1.13 (0.00)</td>
<td>68.06</td>
<td>76.13</td>
<td>0.89 (0.00)</td>
<td>50.00</td>
<td>46.43</td>
<td>1.07 (0.60)</td>
</tr>
</tbody>
</table>

NB: See NB of Table 5.1.
Table 5.3: Out-of-sample forecasts of the behavioural forecasting rule for the S&P500

<table>
<thead>
<tr>
<th>Horizon (in days)</th>
<th>RMSE</th>
<th>RMSE RW</th>
<th>U-Theil</th>
<th>MAE</th>
<th>MAE RW</th>
<th>U-Theil</th>
<th>%DirCh</th>
<th>%DirCh RW</th>
<th>U-Theil</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12,23</td>
<td>12,24</td>
<td>0,99 (0,00)</td>
<td>7,74</td>
<td>7,76</td>
<td>0,99 (0,97)</td>
<td>58,62</td>
<td>50,57</td>
<td>1,15 (0,17)</td>
</tr>
<tr>
<td>5</td>
<td>23,10</td>
<td>23,02</td>
<td>1,00 (0,00)</td>
<td>1,96</td>
<td>17,07</td>
<td>0,11 (0,00)</td>
<td>51,72</td>
<td>50,57</td>
<td>1,02 (0,65)</td>
</tr>
<tr>
<td>10</td>
<td>30,14</td>
<td>30,45</td>
<td>0,98 (0,00)</td>
<td>0,02</td>
<td>22,50</td>
<td>0,00 (0,00)</td>
<td>54,02</td>
<td>51,72</td>
<td>1,04 (0,65)</td>
</tr>
<tr>
<td>21</td>
<td>50,07</td>
<td>48,90</td>
<td>1,02 (0,00)</td>
<td>9,18</td>
<td>35,52</td>
<td>0,25 (0,00)</td>
<td>51,72</td>
<td>50,57</td>
<td>1,02 (0,81)</td>
</tr>
<tr>
<td>63</td>
<td>102,65</td>
<td>96,63</td>
<td>1,06 (0,02)</td>
<td>28,03</td>
<td>71,06</td>
<td>0,39 (0,00)</td>
<td>50,59</td>
<td>49,41</td>
<td>1,02 (0,81)</td>
</tr>
<tr>
<td>126</td>
<td>175,22</td>
<td>157,51</td>
<td>1,11 (0,03)</td>
<td>61,51</td>
<td>114,20</td>
<td>0,53 (0,00)</td>
<td>48,78</td>
<td>50,00</td>
<td>0,97 (0,81)</td>
</tr>
<tr>
<td>252</td>
<td>299,29</td>
<td>240,46</td>
<td>1,24 (0,02)</td>
<td>153,61</td>
<td>188,30</td>
<td>0,81 (0,00)</td>
<td>52,00</td>
<td>51,32</td>
<td>1,01 (0,89)</td>
</tr>
<tr>
<td>504</td>
<td>490,13</td>
<td>325,58</td>
<td>1,50 (0,01)</td>
<td>322,65</td>
<td>279,99</td>
<td>1,15 (0,00)</td>
<td>53,13</td>
<td>51,56</td>
<td>1,03 (0,79)</td>
</tr>
<tr>
<td>756</td>
<td>565,40</td>
<td>328,78</td>
<td>1,71 (0,00)</td>
<td>428,23</td>
<td>310,78</td>
<td>1,37 (0,00)</td>
<td>55,77</td>
<td>53,85</td>
<td>1,03 (0,78)</td>
</tr>
<tr>
<td>1260</td>
<td>938,27</td>
<td>331,10</td>
<td>2,83 (0,00)</td>
<td>836,27</td>
<td>289,76</td>
<td>2,88 (0,00)</td>
<td>46,43</td>
<td>50,00</td>
<td>0,92 (0,73)</td>
</tr>
</tbody>
</table>

NB: See NB of Table 5.1.

In tables 5.1, 5.2 and 5.3, the bold cells are the ones where forecast errors are lower for the behavioural forecasting rule than for the random walk.

For the euro/dollar market, the behavioural forecasting rule (BFR) provides better out-of-sample asset value forecasts (RMSE and MAE) than the random walk for each horizon. However the random walk beats the BFR concerning direction forecasts (%DirCh).

For the Eurostoxx, the BFR provides better asset value forecasts especially in the short run (from 1 day to 10 days). Results are mixed concerning direction forecasts: the performances of direction forecasts alternate between the random walk and the BFR across horizons.

For the S&P500, the BFR provides better asset value forecasts than the random walk for almost all horizons and especially in the short run. The BFR also beats the random walk in the majority of cases concerning direction forecasts.

Therefore, analysing and drawing lessons from agents’ behaviours in financial markets has allowed us to derive a rule that provides better asset price forecasts than the simple random walk. Indeed the behavioural forecasting rule improves forecasts not solely for the direction of the dynamics of asset prices but also for future values of asset prices. This observation stands in the long run as well as in the short run.
6. Conclusion

In this paper, we analyse heterogeneous agents’ behaviours and their determinants in the foreign exchange market and in stock markets. Results show that behaviours’ heterogeneity significantly explains asset price dynamics in the foreign exchange market and in stock markets. We show that heterogeneous behaviours are homogenous across markets. The homogeneity of behaviours between the foreign exchange market and stock markets becomes more acute through the process of financial integration. However, the contagion of behaviours remains significant and strong within markets that trade the same asset (here between the European and US stock markets) but weaker or even not significant between two markets that trade different assets (here between either the European or the US stock markets, and the foreign exchange market). We then analyse which variables determine heterogeneous behaviours. We find that risk aversion (as proxied by the implied volatility on option prices) is more likely to explain heterogeneous behaviours in financial markets than macroeconomic fundamentals. Thus our empirical results support the theoretical model of De Grauwe and Grimaldi (2007) rather than the model of Frankel and Froot (1986). We show that when risk aversion is higher than a critical value, fundamentalists dominate the market. Conversely, when risk aversion is lower than this critical value, the market is globally chartist. Based on this stylised fact we build a behavioural forecasting rule. This rule provides better out-of-sample forecasts of future asset prices than the random walk. This observation stands in the long run as well as in the short run. Further, this observation proves that taking account of stylised facts about agents’ behaviours is useful for explaining and forecasting asset price dynamics.


A. Heterogeneous expectations in the foreign exchange market: empirical proofs

By analysing the behaviour of agents in the foreign exchange market, Frankel and Froot (1987, 1990a, 1990b) show that two main techniques are used by agents in the foreign exchange market to explain and forecast the dynamics of exchange rates. In the short run, agents use chartist techniques while in the long run agents rely on fundamentalist analyses. Chartists build their forecasting rule by interpolating past dynamics of exchange rates. Fundamentalists rely on macroeconomic fundamentals to predict the future path of exchange rates. The observation of Frankel and Froot comes as a stylised fact since later surveys undertaken in every foreign exchange places around the world confirm the observation of Frankel and Froot (see table A).

<table>
<thead>
<tr>
<th>Surveys</th>
<th>Markets</th>
<th>Techniques to Forecast Exchange Rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frankel and Froot (1987, 1990a, 1990b)</td>
<td>United States</td>
<td>- Chartist Analysis (1 month ≤ H ≤ 4 months)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Fundamental Analysis (4 months ≤ H ≤ 12 months)</td>
</tr>
<tr>
<td>Allen and Taylor (1990,1992)</td>
<td>London</td>
<td>- Technical analysis (H ≤ 1 week) for 90 % of respondents</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(chartist analysis ≥ fundamentals for 60 % of agents)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Fundamental analysis (H ≥ 1 year) for 30 % of respondents</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(fundamental analysis &gt; chartist analysis for 85 % of agents)</td>
</tr>
<tr>
<td>Lui and Mole (1998)</td>
<td>Hong-Kong</td>
<td>- Technical analysis (H ≤ 3 months)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Fundamental analysis (H ≥ 6 months)</td>
</tr>
<tr>
<td>Cheung and Wong (2000)</td>
<td>Hong-Kong, Singapore, Tokyo</td>
<td>- Technical analysis (H ≤ 3 months)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Fundamental analysis (H ≥ 6 months)</td>
</tr>
<tr>
<td>Cheung and Chinn (2001)</td>
<td>United States</td>
<td>- Technical analysis (H ≤ 6 months)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Fundamental analysis (H ≥ 6 months)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- 30 % of respondents are systematically chartists</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- 25 % of respondents are systematically fundamentalists</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Fundamental analysis (H ≥ 6 months)</td>
</tr>
</tbody>
</table>

NB: H stands for the investment horizon
B. The theoretical explanation of the over-appreciation of the US dollar in the 1980s by Frankel and Froot (1986)

Frankel and Froot (1986) use their model to explain the appreciation of the US dollar in the mid-1980s. Figure B.1 shows that the dollar wanders away from its fundamental value from January 1984 until January 1988. To explain the over-appreciation of the dollar, Frankel and Froot cut the period January 1980-December 1987 into three stages.

Between January 1980 and December 1982, the dollar appreciation is explained by increases in the real interest rate differential in favour of the United States (figure B.2). Between, January 1983 and June 1985, the dollar keeps appreciating although the real interest rate differential increases in favour of Europe (figure B.2).

Between January 1983 and June 1985, Frankel and Froot relate the appreciation of the dollar to an “endogenous takeoff of a speculative bubble”. Indeed, from January 1983 to June 1985, the appreciation of the dollar is not explained by fundamentals. Thus agents who used fundamentalist rules to forecast the future path of the dollar experience losses. Frankel and Froot add that “fundamentalists have misforecast for so long that they have lost credibility”. Hence because the losses induced by the use of fundamentalist rules, market agents have an incentive to switch to chartist rules. As the proportion of chartists increases in the market, the bubble inflates further more and the exchange rate wanders away from its fundamental value (figure B.1).

Figure B.1: Euro/dollar exchange rate and its fundamental value

Figure B.2: Euro/dollar exchange rate, US and European real interest rates

NB: In figures B.1 and B.2, the black line represents the euro/dollar exchange rate; in figure B.1, the grey line represents the fundamental exchange rate as defined by the BEER model (see appendices E and F); in figure B.2, the light grey line and the dark grey line represent respectively the short term and the long term real interest rate differential between the Euro zone and the United States.
From July 1985 until December 1987, the dollar returns progressively towards its fundamental value. Frankel and Froot attribute the trend reversal in the dollar to the “ever-worsening current account deficit” in the United States (figures B.3 and B.4). During the convergence of the dollar towards its fundamental value, the profitability of the fundamentalist rule increases leading to a rise in the proportion of fundamentalists in the market. The dollar reaches its fundamental value in December 1987 and the bubble disappears.

![Figure B.3: Euro/dollar exchange rate, US and European current account balances](image1)

![Figure B.4: Euro/dollar exchange rate, US and European external debt](image2)

NB: In figures B.3 and B.4, the black line represents the euro/dollar exchange rate; in figure B.3, the light grey and the dark grey lines represent the current account balances respectively in Europe and in the United States; in figure B.4, the light grey and the dark grey lines represent the external debt over GDP respectively in Europe and in the United States.

C. Description of the theoretical model of De Gauwe and Grimaldi (2007)

The model of De Gauwe and Grimaldi (2007) relies on two agents: chartists and fundamentalists.

Chartists interpolate past trends of exchange rates to forecast the future dynamics of currency prices:

\[ E_{c,t}(\Delta s_{t+1}) = \beta \Delta s_t \quad 0 < \beta < 1 \quad (C.1) \]

Thus, when the exchange rate has appreciated (depreciated) in the past, chartists will expect a further appreciation (depreciation) of the currency. Chartists’ behaviour thus accentuates the dynamics of exchange rates. The parameter \( \beta \) represents the degree of interpolation. The higher \( \beta \), the higher the influence of past dynamics of exchange rates on the behaviour of chartist agents.

Fundamentalists forecast future exchange rates based on the spread between the current exchange rate \( s_t \) and the fundamental exchange rate \( s_t^* \):

\[ E_{f,t}(\Delta s_{t+1}) = \psi (s_t - s_t^*) \quad \psi > 0 \quad (C.2) \]

Thus, when the current exchange rate wanders away from its fundamental value, fundamentalists expect a return of the exchange rate towards the fundamental exchange rate. For example if the exchange rate is over-appreciated (under-appreciated) relative to its fundamental value, fundamentalists expect the currency to depreciate (appreciate). The parameter \( \psi \) represents the speed at which the exchange rate returns towards its fundamental value. The higher \( \psi \) the stronger the return force of exchange rates towards their fundamental value.

De Gauwe and Grimaldi (2007) assume that the fundamental exchange rate follows a random walk:

\[ s_t^* = s_{t-1}^* + \epsilon_t \quad (C.3) \]

Where \( \epsilon_t \) is a white noise process
The weight that market agents attribute to a given rule depends on the profitability of a particular rule\textsuperscript{70}. The more profitable a given rule, the higher the weight agents attach to this rule. Chartist and fundamentalist weights are defined as:

\[
\omega_{c,t} = \frac{\exp(\gamma \pi'_{c,t})}{[\exp(\gamma \pi'_{c,t}) + \exp(\gamma \pi'_{f,t})]} \quad \text{and} \quad \omega_{f,t} = \frac{\exp(\gamma \pi'_{f,t})}{[\exp(\gamma \pi'_{c,t}) + \exp(\gamma \pi'_{f,t})]}
\]

(C.4)

Where \(\omega_{f,t} + \omega_{c,t} = 1\) and \(0 < \gamma < 1\)

The parameter \(\gamma\) represents the intensity at which agents revise their forecasting rules. When \(\gamma \to \infty\), agents choose the rule which proves to be the most profitable. Conversely, when \(\gamma \to 0\), agents keep the rule they are using and are insensitive to the profitability of the rules. Thus \(\gamma\) can be viewed as representing the status quo bias in agents’ behaviour. The status quo bias highlighted by Kahneman and Knetsch (1991) means that when agents use a given rule, they find it difficult to change for a different rule.

The profitability \(\pi'_{i,t}\) of each rule is evaluated according to the profit \(\pi_{i,t}\) and the risk \(\sigma^2_{i,t}\) related to this rule:

\[
\pi'_{i,t} = \pi_{i,t} - \mu \sigma^2_{i,t} \quad i = c, f \quad \text{(C.5)}
\]

The parameter \(\mu\) represents the coefficient of risk aversion. The risk associated to a forecasting rule is defined as the variance of the forecasting error:

\[
\sigma^2_{i,t} = [E_{t-1}(s_t) - s_t]^2 \quad i = c, f \quad \text{(C.6)}
\]

\textsuperscript{70} In Frankel and Froot (1986), market agents compute the weight attributed to a given rule based on the past degree of forecasting accuracy of the rules.
The profit $\pi_{i,t}$ related to a forecasting strategy is defined as the one-period earnings of investing one unit of domestic currency in the foreign asset:

$$\pi_{i,t} = [s_i(1 + r^*) - s_{t-1}(1 + r)] \text{sgn}[E_{t+1}(s_i)(1 + r^*) - s_{t-1}(1 + r)] \quad i = c,f \quad (C.7)$$

Where

$$\text{sgn}[x] = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}$$

Thus when agents forecast an appreciation of the foreign currency (an increase in $s_i$) they will invest in the foreign country. If this appreciation is realised then the profit is equal to the appreciation of the foreign currency, corrected by the interest rate differential. Conversely, if a depreciation is realised (a decrease in the exchange rate $s_i$), then agents will face a loss which equals the depreciation of the foreign currency, adjusted by the interest rate differential.

The expected exchange rate at time $t+1$ is obtained by aggregating agents’ forecasts in the market:

$$E_t(\Delta s_{t+1}) = \omega_f E_f(t)(\Delta s_{t+1}) + \omega_c E_c(t)(\Delta s_{t+1})$$

$$\leftrightarrow E_t(\Delta s_{t+1}) = -\omega_f \psi(s_t - s_t^*) + \omega_c \beta \Delta s_t$$

$$\leftrightarrow \Delta s_{t+1} = -\omega_f \psi(s_t - s_t^*) + \omega_c \beta \Delta s_t + \varepsilon_{t+1} \quad (C.8)$$

Figures C.1 and C.2 show the stochastic simulations of the above model (equations (C.1) to (C.8)).
When the chartist rule becomes more profitable than the fundamentalist rule ($\pi'_{c,t} > \pi'_{f,t}$), the chartist weight $\omega_{c,t}$ increases while the fundamentalist weight decreases ($\omega_{f,t} = 1 - \omega_{c,t}$). The bubble inflates: the exchange rate $s_t$ wanders away from its fundamental value $s_t^\ast$. At a given period of time, a shock will reverse the trend in the exchange rate. The exchange rate starts to return towards its fundamental level. The fundamentalist rule becomes more profitable than the chartist rule ($\pi'_{c,t} < \pi'_{f,t}$). The chartist weight $\omega_{c,t}$ decreases while the fundamentalist weight increases. As the proportion of fundamentalists increases in the market the exchange rate $s_t$ returns progressively towards its fundamental value $s_t^\ast$.

Therefore, the interaction between chartists and fundamentalists explain the swings of the exchange rate relative to its fundamental value across time. They explain why exchange rates wander away and then return towards their fundamental value. Thus, such models allow
explaining the formation of bubbles in the foreign exchange market \textit{i.e.} the disconnections of exchange rates from their fundamental value.

One of the limits of the above model is that the trend reversals in the exchange rate remain exogenous. To overcome this limit and to endogenise the trend reversals in exchange rates, two main factors have been put forward by the literature: the dynamics of fundamentals (Frankel and Froot (1986), De Grauwe and Grimaldi (2007)) and the degree of risk aversion (De Grauwe and Grimaldi (2007)).

De Grauwe and Grimaldi endogenise the trend reversal of the exchange rate towards its fundamental value by using a stylised fact observed in agents’ behaviour: the more agents realise losses, the more they are willing to take risks. This stylised fact has been highlighted by Kahneman and Tversky (1979) in the prospect theory. Prospect theory is formalised as follows:

\[
\mu_{i,t} = \mu / [1 + \Phi' |\pi^*_i,t|] \quad i = c, f \quad (C.9)
\]

Where \(\pi^*_i,j = (1 - \rho)\sum_{j=0}^{\infty} \rho^j (\pi_{i,j-1})\) \(i = c, f\)

De Grauwe and Grimaldi (2007) show that when exchange rates move away from their fundamental value, fundamentalists realise losses (\(\pi^*_{i,t} < 0\) in (C.9)). Such losses lower the risk aversion of fundamentalists (\(\mu_{i,t}\) in (C.9)) and lead them to use their rule more often. The increase in the use of the fundamentalist rule in turn triggers the return of the exchange rate towards its fundamental value. The use of fundamentalist rules becomes more profitable and hence leads to an increase in the proportion of fundamentalists in the market. Although the explanation of De Grauwe and Grimaldi rests on a stylised fact, testing their proposition remains a difficult task. Indeed, we need a measure of risk aversion for fundamentalists and chartists respectively. Besides, as risk aversion tends to propagate between agents in the markets (Boschi and Goenka (2007)), doubts arise on the mechanism put forward by De Grauwe and Grimaldi (2007). Hence when risk aversion increases for fundamentalists it should also increase for chartists.
A more relevant factor has been proposed by Frankel and Froot (1986) and later by De Grauwe and Grimaldi (2007). The trend reversal is here triggered by macroeconomic fundamentals and especially the stock of external debt \(Z_t\) through current account imbalances. The fundamental exchange rate is related to the difference between the stock of external debt in the domestic country and in the foreign country \((Z_t - Z_t^*)\) by an elasticity coefficient \(\varepsilon\):

\[
(Z_t - Z_t^*) = -\varepsilon (s_t - s_{t,t}^*)
\]  
(C.10)

When the exchange rate depreciates and is undervalued \((s_t < s_{t,t}^*)\), the economy becomes more competitive: exports increase and imports decrease leading to an excess in the current account balance. In other words, there is an excess of foreign assets supply or equivalently an excess of the demand for domestic assets \((Z_t > Z_t^*)\). This excess in the demand for domestic assets leads to an appreciation of the domestic currency. The exchange rate returns towards its fundamental value. The introduction of such a mechanism in the model increases the return force of the exchange rate towards its fundamental value (Frankel and Froot (1986), De Grauwe and Grimaldi (2007)). The higher \(\varepsilon\) the stronger the return force induced by macroeconomic fundamentals on the exchange rate.

**D. Description of the empirical model of Vigfusson (1997)**


\[
\Delta s_t = \begin{cases} 
  f + \theta(\bar{s}_{t-1} - s_{t-1}) + \beta(i_{t-1} - i_{t-1}^*) + \varepsilon_t^f c + \psi(ma_{1.4,t-1} - ma_{200,t-1}) + \Gamma(i_{t-1} - i_{t-1}^*) + \varepsilon_t^c & \text{if } S_t = f \\
  c + \varepsilon_t^c & \text{if } S_t = c 
\end{cases}
\]

With \(s_t\), the (log of the) exchange rate; \(\bar{s}_t\), the (log of the) fundamental exchange rate; \(ma_{t,t}\), the moving average of the (log of the) exchange rate in the period \(\tau\); \((i_{t,t} - i_{t,t}^*)\), the one-month interest rate differential between Canada and the United States; \(\varepsilon_t^c \rightarrow N(0, \sigma^c)\) and \(\varepsilon_t^f \rightarrow N(0, \sigma^f)\); \(c\) and \(f\) are constants.
Vigfusson (1997) relied on two estimates for the fundamental exchange:

- a measure of purchasing power parity: \( \bar{s}_t = p_t - p_t^* \)
- an error correction model based on the terms of trade taken from Amano and Van Norden (1995):

\[
\Delta q_t = \nu [q_{t-1} - \gamma_0 - \gamma_1 \text{TOTCOMOD}_{t-1} + \text{TOTENERGY}_{t-1}] + \lambda_1 \text{DIFF}_{t-1} + \epsilon_t
\]

With \( q_t \), the (log of the) Canada-US real exchange rate; \( \text{TOTCOMOD}_t \), the price of exported non-energy commodities divided by the price of imported manufactured goods; \( \text{TOTENERGY}_t \), the price of exported energy commodities divided by the price of imported manufactured goods; \( \text{DIFF}_t \), the interest rate differential between the Canada and the United States (\( \text{DIFF}_t = (i_t^{st} - i_t^{lt}) - (i_t^{st*} - i_t^{lt*}) \)).

We estimate the model of Vigfusson for the synthetic euro/dollar exchange rate in daily frequency for a period that spans January 1978 to December 1996. The fundamental exchange rate is estimated based on a BEER model (see appendices E and F). Table D.1 summarises the results of the estimation with the EM algorithm.

Table D.1: Results associated to the original model of Vigfusson applied to the euro/dollar exchange rate over the period January 1978 - December 1996

<table>
<thead>
<tr>
<th>States</th>
<th>Coefficients</th>
<th>State Variances</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fundamentalist ((S_t = f))</td>
<td>( f )</td>
<td>( \theta )</td>
</tr>
<tr>
<td>([-1.02] )</td>
<td>( 5.74 \times 10^{-4} )</td>
<td>( [3.62] )</td>
</tr>
<tr>
<td>Chartist ((S_t = c))</td>
<td>( c )</td>
<td>( \Psi )</td>
</tr>
<tr>
<td>([-0.84] )</td>
<td>( 4.45 \times 10^{-4} )</td>
<td>( [2.23] )</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; critical values for the test of Student amount to 1.96 at a 5% confidence level and to 1.64 at a 10% confidence level.

The fundamentalist rule tells us that if the dollar is overvalued \(( (\bar{s}_{t-1} - s_{t-1}) > 0 )\), then fundamentalists expect a depreciation of the dollar. The chartist rule shows that if the dollar has appreciated in the recent past \(( (ma_{14,t-1} - ma_{200,t-1} ) < 0 )\), then chartists expect a further appreciation of the dollar. The long run interest rate differentials appear unsignificant whether in the fundamentalist regime or in the chartist regime. We find that the state probabilities are higher in the fundamentalist regime than in the chartist one. Thus fundamentalists dominate...
the market in periods of high exchange rate volatility while chartists dominate in periods of low exchange rate volatility.

Table D.2: Conditional probabilities, unconditional probabilities and regime duration

<table>
<thead>
<tr>
<th>States</th>
<th>Conditional Probabilities</th>
<th>Unconditional Probabilities</th>
<th>Regime Expected Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fundamentalist</td>
<td>$p = 0.76$</td>
<td>$\pi_f = 0.47$</td>
<td>$d_f = 4.16$ days</td>
</tr>
<tr>
<td>Chartist</td>
<td>$q = 0.79$</td>
<td>$\pi_c = 0.54$</td>
<td>$d_c = 4.76$ days</td>
</tr>
</tbody>
</table>

NB: $p = P(S_t=f|S_{t-1}=c)$; $q = P(S_t=c|S_{t-1}=f)$; $\pi_f = (1-q)/(2-p-q)$; $\pi_c = (1-p)/(2-p-q)$; $d_f = 1/(1-p)$; $d_c = 1/(1-q)$.

Conditional probabilities show that when agents are fundamentalist in the past, there is a higher probability that they will be chartist in the future ($p < q$). Over the period, the probability to be in the fundamentalist state amounts to 0.47 while the probability to be in the chartist state amounts to 0.54 ($\pi_f < \pi_c$). Besides, the duration of the fundamentalist regime is slightly shorter than the duration of the chartist regime ($d_f > d_c$).

Table D.3: Diagnostic tests for the original Vigfusson’s model

<table>
<thead>
<tr>
<th>Diagnostic Tests</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Likelihood $lnL$</td>
<td>23202.69</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Autocorrelation Tests ($H_0$: No Autocorrelation)</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime 1</td>
<td>5.01 (0.03)</td>
</tr>
<tr>
<td>Regime 2</td>
<td>1.44 (0.23)</td>
</tr>
<tr>
<td>Both Regimes</td>
<td>2.74 (0.10)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Heteroscedasticity Tests ($H_0$: Homoscedasticity)</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regime 1</td>
<td>2.65 (0.10)</td>
</tr>
<tr>
<td>Regime 2</td>
<td>33.36 (0.00)</td>
</tr>
<tr>
<td>Both Regimes</td>
<td>4.90 (0.03)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Linearity Test ($H_0$: Linear Model)</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50.61 (0.00)</td>
</tr>
</tbody>
</table>

NB: Autocorrelation tests and heteroscedasticity tests follow a $\chi^2(1)$; linearity test follows a $\chi^2(4)$. The critical values for a $\chi^2(1)$ amount to 2.70 and 3.84 respectively at a 10 % and 5 % confidence level. The critical values for a $\chi^2(4)$ amount to 7.77 and 9.48 respectively at a 10 % and 5 % confidence level; $p$-values are mentioned in brackets.

Diagnostic tests show no autocorrelation in both regimes. However, ARCH tests validate the presence of heteroskedasticity in the variance of residuals. Besides, we reject the hypothesis of the use of a non-linear Markov structure of order one. This result is often observed in studies using a Markov switching structure of order one (Vigfusson (1997), Bessec and Robineau (2003)). Those studies suggest considering more than two states. In the case of the heterogeneous agents model, we could consider a transition state between the fundamentalist and the chartist regimes.
Figure D.1 represents the smoothed probabilities of being in the fundamentalist regime between January 1978 and December 1996. We observe that when the probability of being fundamentalist is close to one, the exchange rate returns towards its fundamental value. Conversely, when the probability of being fundamentalist is close to zero, the exchange rate wanders away from its fundamental value.

**Figure D.1: Euro/dollar dynamics and smoothed probabilities of being in the fundamentalist state** $P(S_t=f/I_t)$ **between January 1978 and December 1996**

NB: The black line represents the exchange rate (right scale); the grey line represents the Hodrick-Prescott (HP) filtered fundamental exchange rate estimated with a BEER model (right scale); the grey line represents the smoothed probabilities (left scale), the black line and the orange lines represent the HP filtered smoothed probabilities with respectively $\lambda = 1500$ and $\lambda = 100000$.

E. Description of the variables used in the BEER, UIP and UIP-URP models

**E.1 Endogenous variable: the real exchange rate**

$$q_t = \log(Q_t) = \log(S_t/P_t^*))$$

With $S_t$, the euro/dollar exchange rate (1 euro for $S$ dollars); $P_t^*$, the consumer price index in the United States; $P_t$, the consumer price index in the Euro zone.
E.2 Exogenous variables

- The long term interest rate differential:

\[(r_t - r_t^*) = (i_t - \pi_t) - (i_t^* - \pi_t^*)\]

With \(\pi_t = [CPI_t - CPI_{t-12}/ CPI_{t-12}] \times 100\) and \(\pi_t^* = [CPI_t^* - CPI_{t-12}^*/ CPI_{t-12}^*] \times 100\); \(i_t\) and \(i_t^*\), respectively the nominal interest rates on 10-years bond for the Euro zone and the United States; \(\pi_t\) and \(\pi_t^*\), the inflation rates in the Euro zone and in the United States computed as the growth rate of the consumer price index in the Euro zone \((CPI_t)\) and in the United States \((CPI_t^*)\).

- The oil price index:

\[op_t = \log(OPI_t/CPI_t^*)\]

With \(OPI_t\), the price of the North Sea brent (the brent is listed in US dollars); \(CPI_t^*\), the consumer price index in the United States.

- The productivity differential:

\[(a_t - a_t^*) = \log(GDP_t/L_t) - \log(GDP_t^*/L_t^*)\]

With \(GDP_t\) and \(GDP_t^*\), the gross domestic product in the Euro zone and in the United States; \(L_t\) and \(L_t^*\), the number of employed people in the Euro zone and in the United States.

- The net international investment position differential:

\[(niip_t - niip_t^*) = NIIP_t/GDP_t - NIIP_t^*/GDP_t^*\]

With \(NIIP_t\) and \(NIIP_t^*\) respectively, the net international investment position of the Euro zone and the United States; \(GDP_t\) and \(GDP_t^*\), the gross domestic product in the Euro zone and in the United States. The series \((niip_t - niip_t^*)\) have been filtered with a Hodrick-Prescott filter \((\lambda = 14400)\). This filter is often used in the literature to smooth series available
at lower frequencies. Indeed, the BEER model is estimated on a monthly frequency while data are only available annually. Besides, the use of such a variable without filtering leads to an incorrect sign in equation (3b) in the core text.

- The stock price index differential:

\[(sp_t - sp_t^*) = \log(SP_t/CPI_t) - \log(SP_t^*/CPI_t^*)\]

With \(SP_t\) and \(SP_t^*\) respectively, the stock price indices in the Eurozone (the Eurostoxx) and in the United States (the S&P500); \(CPI_t\) and \(CPI_t^*\), the consumer price indices in the Eurozone and in the United States.

F. Procedure for the estimation of the fundamental exchange rate with a BEER model, a UIP model and a UIP-URP model

The estimation procedure of the models follows three steps. The first step checks whether all series have the same order of integration. Table F.1 shows that all series are integrated of order one.

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>(q_t)</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>((r_t - r_t^*))</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>((a_t - a_t^*))</td>
<td>I(1)</td>
<td>I(2)</td>
<td>I(1)</td>
</tr>
<tr>
<td>((niip_t - niip^*_t))</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>((sp_t - sp_t^*))</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>(op_t)</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
</tbody>
</table>

In a second step, we look for the number of cointegrated vectors by applying Trace tests and Maximum Eigenvalue tests. Results available in table F.2 (column 4) validate the presence of at most one cointegrated vector between the exchange rate and its fundamentals. We therefore estimate a univariate error correction model.
Table F.2: Number of cointegrated vectors at a 5 % confidence level for the exchange rate models

<table>
<thead>
<tr>
<th></th>
<th>BEER model</th>
<th></th>
<th>UIP-URP model</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data Trend</td>
<td>Type de Test</td>
<td>Intercept</td>
<td>No Intercept No Trend</td>
</tr>
<tr>
<td></td>
<td>None</td>
<td>No Intercept No Trend</td>
<td>Linear</td>
<td>Intercept No Trend</td>
</tr>
<tr>
<td>Trace</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Max-Eigenvalue</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

|                         |                       | No Intercept No Trend  | Intercept     | No Intercept No Trend  |
|                         |                       | Linear                 | Intercept     | Linear                 |
|                         |                       | Quadratic              | Intercept     | Trend                  |
| Trace                   | 1                      | 1                      | 1             | 1                      |
| Max-Eigenvalue          | 1                      | 1                      | 1             | 1                      |

NB: Critical values are based on the tables of MacKinnon, Haug and Michelis (1999).

In a third step, we estimate the long run relationships by ordinary least squares (OLS).

The long-run relationships are defined as follows:

- **UIP model:** \[ \tilde{q}_t = \beta_0 + \beta_1 (r_t - r_t^*) + \epsilon_t \]

- **BEER model:** \[ \tilde{q}_t = \beta_0 + \beta_1 (r_t - r_t^*) + \beta_2 (a_t - a_t^*) + \beta_3 (niip_t - niip_t^*) + \epsilon_t \]

- **UIP-URP model:** \[ \tilde{q}_t = \beta_0 + \beta_1 (r_t - r_t^*) + \beta_2 (sp_t - sp_t^*) + \beta_3 op_t + \epsilon_t \]

With \( \tilde{q}_t \), the (log of the) real euro/dollar exchange rate (s dollars for 1 euro); \((r_t - r_t^*)\), the long term interest rate differential; \((a_t - a_t^*)\), the productivity differential; \((niip_t - niip_t^*)\), the differential of the ratio of the net international investment positions over GDP; \((sp_t - sp_t^*)\), the stock price indices differential; \(op_t\), the oil price index; \(\epsilon_t\), an error term.

We then test for the stationarity of residuals in the long run relationships. Table F.3 to F.5 show that residuals in the long run relationships are stationary.
Table F.3: Critical values for Augmented Dickey Fuller cointegration test
(UIP model (3a) in the core text)

<table>
<thead>
<tr>
<th>Tables</th>
<th>Confidence Level</th>
<th>1 %</th>
<th>5 %</th>
<th>10 %</th>
<th>T-Stat (3a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engle and Yoo (1987)</td>
<td>T = 380, N = 1</td>
<td>-4.00</td>
<td>-3.37</td>
<td>-3.02</td>
<td>-3.87</td>
</tr>
<tr>
<td>Phillips and Ouliaris (1990)</td>
<td>without constant, without trend</td>
<td>-3.39</td>
<td>-2.76</td>
<td>-2.45</td>
<td>-3.87</td>
</tr>
<tr>
<td></td>
<td>with constant, without trend</td>
<td>-3.96</td>
<td>-3.37</td>
<td>-3.07</td>
<td>-3.87</td>
</tr>
<tr>
<td></td>
<td>with constant, with trend</td>
<td>-4.36</td>
<td>-3.80</td>
<td>-3.52</td>
<td>-3.94</td>
</tr>
<tr>
<td>McKinnon (1991)</td>
<td>with constant, without trend</td>
<td>-3.93</td>
<td>-3.35</td>
<td>-3.06</td>
<td>-3.87</td>
</tr>
<tr>
<td></td>
<td>with constant, with trend</td>
<td>-4.37</td>
<td>-3.81</td>
<td>-3.51</td>
<td>-3.94</td>
</tr>
</tbody>
</table>

Table F.4: Critical values for Augmented Dickey Fuller cointegration test
(BEER model (3b) in the core text)

<table>
<thead>
<tr>
<th>Tables</th>
<th>Confidence Level</th>
<th>1 %</th>
<th>5 %</th>
<th>10 %</th>
<th>T-Stat (3b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engle and Yoo (1987)</td>
<td>T = 392, N = 3</td>
<td>-4.34</td>
<td>-3.78</td>
<td>-3.51</td>
<td>-3.60</td>
</tr>
<tr>
<td>Phillips and Ouliaris (1990)</td>
<td>without constant, without trend</td>
<td>-4.30</td>
<td>-3.74</td>
<td>-3.44</td>
<td>-4.60</td>
</tr>
<tr>
<td></td>
<td>with constant, without trend</td>
<td>-4.73</td>
<td>-4.11</td>
<td>-3.83</td>
<td>-4.40</td>
</tr>
<tr>
<td></td>
<td>with constant, with trend</td>
<td>-5.04</td>
<td>-4.49</td>
<td>-4.20</td>
<td>-4.40</td>
</tr>
<tr>
<td></td>
<td>with constant, with trend</td>
<td>-5.03</td>
<td>-4.47</td>
<td>-4.18</td>
<td>-4.40</td>
</tr>
</tbody>
</table>

Table F.5: Critical values for Augmented Dickey Fuller cointegration test
(UIP-URP model (3c) in the core text)

<table>
<thead>
<tr>
<th>Tables</th>
<th>Confidence Level</th>
<th>1 %</th>
<th>5 %</th>
<th>10 %</th>
<th>T-Stat (3c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engle and Yoo (1987)</td>
<td>T = 335, N = 3</td>
<td>-4.34</td>
<td>-3.78</td>
<td>-3.51</td>
<td>-4.76</td>
</tr>
<tr>
<td>Phillips and Ouliaris (1990)</td>
<td>without constant, without trend</td>
<td>-4.30</td>
<td>-3.74</td>
<td>-3.44</td>
<td>-4.76</td>
</tr>
<tr>
<td></td>
<td>with constant, without trend</td>
<td>-4.73</td>
<td>-4.11</td>
<td>-3.83</td>
<td>-4.76</td>
</tr>
<tr>
<td></td>
<td>with constant, with trend</td>
<td>-5.04</td>
<td>-4.49</td>
<td>-4.20</td>
<td>-4.52</td>
</tr>
<tr>
<td>McKinnon (1991)</td>
<td>with constant, without trend</td>
<td>-4.70</td>
<td>-4.13</td>
<td>-3.84</td>
<td>-4.76</td>
</tr>
<tr>
<td></td>
<td>with constant, with trend</td>
<td>-5.04</td>
<td>-4.47</td>
<td>-4.18</td>
<td>-4.52</td>
</tr>
</tbody>
</table>

We therefore estimate the error correction models, which are defined as:

- UIP model: \[ \Delta q_t = b_1 \Delta(r_t - r_t^*) + \lambda [\bar{q}_{t-1} - \beta_0 - \beta_1 (r_{t-1} - r_{t-1}^*)] + \epsilon_t \]

- BEER model: \[ \Delta q_t = b_1 \Delta(r_t - r_t^*) + b_2 \Delta(a_t - a_t^*) + b_3 \Delta(niip_t - niip_t^*) \]

\[ + \lambda [\bar{q}_{t-1} - \beta_0 - \beta_1 (r_{t-1} - r_{t-1}^*) - \beta_2 (a_{t-1} - a_{t-1}^*) - \beta_3 (niip_{t-1} - niip_{t-1}^*)] + \epsilon_t \]

- UIP-URP model: \[ \Delta q_t = b_1 \Delta(r_t - r_t^*) + b_2 \Delta(sp_t - sp_t^*) + b_3 \Delta op_t \]

\[ + \lambda [\bar{q}_{t-1} - \beta_0 - \beta_1 (r_{t-1} - r_{t-1}^*) - \beta_2 (sp_{t-1} - sp_{t-1}^*) - \beta_3 op_{t-1}] + \epsilon_t \]
The estimation of the error correction models is based on monthly data for the euro/dollar exchange rate. The period runs from January 1975 to December 2009. We follow the traditional estimation method of Engle and Granger (1987). We take account of the eventual presence of heteroscedasticity and autocorrelation in the residuals by applying the HAC correction of Newey-West (1987). Results are available in table F.6.

### Table F.6: Estimation output for the error correction models

<table>
<thead>
<tr>
<th>Model</th>
<th>$\lambda$</th>
<th>$\beta_0$</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$R^2_{adj}$</th>
<th>$R^2_{adj LT}$</th>
<th>ARCH</th>
<th>LM</th>
<th>J&amp;B</th>
<th>RESET</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEER</td>
<td>-0.026 [2.31]</td>
<td>-0.961</td>
<td>0.086</td>
<td>1.164</td>
<td>0.021</td>
<td>0.04</td>
<td>0.65</td>
<td>3.87 (0.56)</td>
<td>38.77 (0.00)</td>
<td>0.25 (0.88)</td>
<td>0.62 (0.73)</td>
</tr>
<tr>
<td>UIP</td>
<td>-0.025 [-2.79]</td>
<td>-0.485</td>
<td>0.089</td>
<td>X</td>
<td>X</td>
<td>0.04</td>
<td>0.49</td>
<td>4.79 (0.44)</td>
<td>37.63 (0.00)</td>
<td>0.07 (0.96)</td>
<td>1.05 (0.58)</td>
</tr>
<tr>
<td>UIP-URP</td>
<td>-0.033 [-2.46]</td>
<td>-0.699</td>
<td>0.022</td>
<td>0.374</td>
<td>0.037</td>
<td>0.32</td>
<td>0.48</td>
<td>4.06 (0.54)</td>
<td>26.27 (0.00)</td>
<td>5.38 (0.06)</td>
<td>0.20 (0.90)</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; *p*-values are mentioned in brackets; critical values for the test of Student amount to 1.96 at a 5 % confidence level and to 1.64 at a 10 % confidence level; 5 lags are considered for ARCH and LM tests.

Concerning diagnostic tests, LM tests show the presence of autocorrelation in the residuals. ARCH tests show no heteroskedasticity in the variance of residuals. The Jarque and Bera test confirms the normality of the residuals. RESET tests accept the specification of the models.

Adjusted $R^2$ are relatively low in the error correction models. This result is not surprising since it is difficult to explain the variation of the exchange rate with macroeconomic fundamentals. Adjusted $R^2$ are more satisfying in the long run relationships. As a matter of facts, the BEER model explains more than 60 % of the variance of the (log of the) euro/dollar exchange rate.

The coefficients associated to the long run relationship are negative and significant. Thus, the exchange rate can wander away from its fundamental value in the short run, but will converge towards its fundamental value in the long run.

The coefficients of the long run relationship are correctly signed: an increase in the interest rate differential leads to an appreciation of the euro as well as an increase in the productivity differential. Also, an excess in the net international investment position leads to an appreciation of the euro.
To compute the fundamental value of the nominal exchange rate, we consider the estimated real exchange rate \( \bar{q}_t \) from the long run relationship. We then convert it into a nominal exchange rate based on the following relationship:

\[
\bar{s}_t = \bar{q}_t - p_t + p_t^*
\]

We choose to smooth slightly \( \bar{s}_t \) with a Hodrick-Prescott (HP) filter (with \( \lambda = 14000 \)) in order to isolate the permanent component of the exchange rate; i.e. the fundamental exchange rate.

**Table F.7: Estimation characteristics of the fundamental models for the euro/dollar exchange rate**

<table>
<thead>
<tr>
<th>Model</th>
<th>Frequency</th>
<th>Data Transformation</th>
<th>Hodrick-Prescott filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>UIP</td>
<td>Monthly</td>
<td>CPIs filtered from monthly to daily frequency (Quadratic Match Average)</td>
<td>( \lambda = 14000 ) in monthly frequency and then filtered in daily frequency (Quadratic Match Average)</td>
</tr>
<tr>
<td>BEER</td>
<td>Monthly</td>
<td>NIIPs filtered from annually to monthly frequency (Quadratic Match Average)</td>
<td>( \lambda = 14000 ) in monthly frequency and then filtered in daily frequency (Quadratic Match Average)</td>
</tr>
<tr>
<td>UIP-URP</td>
<td>Monthly</td>
<td>CPIs filtered from monthly to daily frequency (Quadratic Match Average)</td>
<td>( \lambda = 14000 ) in monthly frequency and then filtered in daily frequency (Quadratic Match Average)</td>
</tr>
</tbody>
</table>

Concerning the BEER model, since macroeconomic data about external debt are not available in 2009, in order to have a fundamental exchange rate in 2009, we extend the Hodrick-Prescott (HP) filtered fundamental exchange rate by relying on the last monthly growth rate of the HP filtered fundamental exchange rate. We check whether the direction of the fundamental exchange rate in 2009 match the one obtained with UIP (indeed, data on long term interest rates are available until December 2009). Besides, as we test the heterogeneous agents model in daily frequency, we convert the monthly series \( \bar{s}_t \) in a daily series with a Quadratic Match Average filter. Figure F.1 represents the actual dynamics of the euro/dollar exchange rate and the estimated fundamental exchange rates.
We decide to use a weighted average of the estimated fundamental exchange rates. Thus, the definite fundamental exchange rate we use in our heterogeneous agents model ($\tilde{s}_t$) is defined as:

$$\tilde{s}_t = \alpha_1 \tilde{s}^{\text{BEER}}_t + \alpha_2 \tilde{s}^{\text{UIP}}_t + \alpha_3 \tilde{s}^{\text{UIP\textsuperscript{URP}}}_t$$

The coefficients $\alpha_1, \alpha_2, \alpha_3$ are estimated based on an OLS estimator:

$$\hat{\alpha} = \arg \min_{\alpha} \sum_{t=1}^{n} \left( \tilde{s}_t - \alpha_1 \tilde{s}^{\text{BEER}}_t - \alpha_2 \tilde{s}^{\text{UIP}}_t - \alpha_3 \tilde{s}^{\text{UIP\textsuperscript{URP}}}_t \right)^2$$

The final fundamental exchange rate is represented in figure F.2.
Figure F.2: Euro/dollar exchange rate and weighted fundamental exchange rate $\bar{s}_t$

![Figure F.2: Euro/dollar exchange rate and weighted fundamental exchange rate $\bar{s}_t$](image)

NB: The weighted fundamental exchange rate is represented in grey; the actual exchange rate is in black.

The estimated fundamental exchange rate clearly represents the negative bubble on the dollar in the 1980s (highlighted by Frankel and Froot (1986)). Also, the estimated value of the fundamental euro/dollar exchange rate is close to the value of 1 euro per 1 dollar i.e. its official rate at the introduction of the quotation of the euro in January 1999. Finally, estimations show that the depreciation of the euro at the beginning of the 2000s has been too excessive with regards to its fundamental value. This observation was also noticed by the literature on the euro/dollar exchange rate dynamics at that period (Meredith (2001)).

G. Description of the variables used in the long-term level of stock price indices

G.1 Endogenous variable: the real stock price index

$$sp_t^r = \log(SP_t^r) \quad \text{With} \quad SP_t^r = \frac{SP_t}{CPI_t}$$

With $SP_t$, the stock price index of the respective economies; $CPI_t$, the consumer price index in the respective economic zones.
G.2 Exogenous variables

- The real expected profits on stock prices:

\[
\pi_t^{a,r} = \log(\Pi_t^a / CPI_t)
\]

With \(\Pi_t^a\), the expected profits on stock prices computed as the inverse of the price-earning ratio over the stock price index; \(CPI_t\), the consumer price index in the respective economic zones.

- The real interest rate spread:

\[
(r_t^{lt} - r_t^{st}) = (i_t^{lt} - \pi_t) - (i_t^{st} - \pi_t)
\]

With \(i_t^{lt}\), the short term nominal interest rate (3-months Treasury bill) for the respective economic zones; \(i_t^{lt}\), the long term nominal interest rate (10-years Government bond) for the respective economic zones; \(\pi_t\), the inflation rates in the respective economic zones computed as the growth rate of the consumer price index in the respective economic zones (\(\pi_t = \frac{[CPI_t - CPI_{t-12}/ CPI_{t-12}]x100}{100}\)).

- The productivity:

\[
a_t = \log(GDP_t / L_t)
\]

With \(GDP_t\), the gross domestic product in the respective economic zones; \(L_t\), the number of employed people in the respective economic zones.

- The oil price index:

\[
op_t = \log(OP_t / CPI_t^*)
\]

With \(OP_t\), the price of the North Sea brent (the brent is listed in US dollars); \(CPI_t^*\), the consumer price index in the United States.
H. Procedure for the estimation of the fundamental stock price indices

The estimation procedure of the fundamental stock price index follows three steps. The first step checks whether all series have the same order of integration. Table H.1 shows that all series are integrated of order one.

### Table H.1: Integration order of the series in the stock price indices models

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$sP_t^r$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>$(r^d_t - r^f_t)$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>$a_T$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>$op_t$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
</tbody>
</table>

In a second step, we look for the number of cointegrated vectors by applying Trace tests and Maximum Eigenvalue tests. Results available in table H.2 (column 4) validate the presence of at most one cointegrated vector between the stock price indices and their fundamentals. We therefore estimate a univariate error correction model.

### Table H.2: Number of cointegrated vectors at a 5 % confidence level for the stock price indices models

<table>
<thead>
<tr>
<th>Eurostoxx</th>
<th>Eurostoxx</th>
<th>S&amp;P500</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type de Test</td>
<td>Eurostoxx</td>
<td>S&amp;P500</td>
</tr>
<tr>
<td>Trace</td>
<td>No Intercept</td>
<td>No Intercept</td>
</tr>
<tr>
<td>Max-Eigenvalue</td>
<td>No Trend</td>
<td>No Intercept</td>
</tr>
<tr>
<td>Trace</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Max-Eigenvalue</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Trace</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Max-Eigenvalue</td>
<td>2</td>
<td>2</td>
</tr>
</tbody>
</table>

NB: Critical values are based on the tables of MacKinnon, Haug and Michelis (1999).

In a third step, we estimate the long run relationships by ordinary least squares (OLS). The long-run relationship is defined as follows:

$$\overline{sP_t^r} = \beta_0 + \beta_1 \pi_t^a + \beta_2 (r_t^d - r_t^s) + \beta_3 at_t + \beta_4 op_t + \epsilon_t$$
With \( \tilde{r}_t \), the (log of the) real stock price index; \( \pi_{t,a,r} \), the real expected profits on the stock price index; \( (r_{it} - r_{ist}) \), the real interest rate spread; \( a_t \), the productivity; \( op_t \), the oil price index; \( \varepsilon_t \), an error term.

We then test for stationary residuals in the long run relationships. Table H.3 shows that residuals in the long run relationships are stationary.

Table H.3: Critical values for Augmented Dickey Fuller cointegration test

<table>
<thead>
<tr>
<th>Tables</th>
<th>Confidence Level</th>
<th>1 %</th>
<th>5 %</th>
<th>10 %</th>
<th>T-Stat EU</th>
<th>T-Stat US</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engle and Yoo (1987)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T = 330, N = 4</td>
<td>4,47</td>
<td>4,62</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phillips and Ouliaris (1990)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without constant, without trend</td>
<td>-4,67</td>
<td>-4,13</td>
<td>-3,81</td>
<td>-3,89</td>
<td>-3,70</td>
<td>-4,62</td>
</tr>
<tr>
<td>with constant, without trend</td>
<td>-5,07</td>
<td>-4,45</td>
<td>-4,16</td>
<td>-4,47</td>
<td>-4,62</td>
<td>-4,62</td>
</tr>
<tr>
<td>McKinnon (1991)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>with constant, without trend</td>
<td>-5,36</td>
<td>-4,74</td>
<td>-4,46</td>
<td>-4,47</td>
<td>-4,62</td>
<td>-4,62</td>
</tr>
<tr>
<td>with constant, with trend</td>
<td>-5,02</td>
<td>-4,46</td>
<td>-4,16</td>
<td>-4,47</td>
<td>-4,62</td>
<td>-4,62</td>
</tr>
</tbody>
</table>

We therefore estimate the error correction models. The error correction model takes the following form:

\[
\Delta sp_t = b_1 \Delta \pi_{t,a,r} + b_2 \Delta (r_{it} - r_{ist}) + b_3 \Delta a_t + b_4 \Delta op_t
\]

\[+ \lambda [\tilde{r}_{t-1} - \beta_0 - \beta_1 \pi_{t-1,a,r} - \beta_2 (r_{t-1,i} - r_{t-1,ist}) - \beta_3 a_{t-1} - \beta_4 op_{t-1}] + \varepsilon_t\]

The estimation of the error correction model is based on monthly data for the Eurostoxx and the S&P500. The period runs from January 1975 to December 2009. We follow the traditional method of Engle and Granger (1987). We take account of the eventual presence of heteroskedasticity and autocorrelation in the residuals by applying the HAC correction of Newey-West (1987). Results are available in table H.4.

Table H.4: Estimation output for the error correction models

<table>
<thead>
<tr>
<th>Model</th>
<th>( \lambda )</th>
<th>( \beta_0 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \beta_3 )</th>
<th>( \beta_4 )</th>
<th>R2adj</th>
<th>R2adj LT</th>
<th>ARCH</th>
<th>LM</th>
<th>J&amp;B</th>
<th>RESET Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>EU</td>
<td>-0.035</td>
<td>-1.412</td>
<td>0.855</td>
<td>-0.022</td>
<td>2.354</td>
<td>-0.302</td>
<td>0.14</td>
<td>0.04</td>
<td>10.95(0,05)</td>
<td>55.10(0,00)</td>
<td>70.00(0,00)</td>
<td>3.85(0,14)</td>
</tr>
<tr>
<td>US</td>
<td>-0.040</td>
<td>-5.184</td>
<td>0.285</td>
<td>-0.040</td>
<td>3.211</td>
<td>-0.335</td>
<td>0.07</td>
<td>0.03</td>
<td>19.33(0,00)</td>
<td>34.15(0,00)</td>
<td>27.90(0,00)</td>
<td>6.08(0,05)</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; \( p-values \) are mentioned in brackets; critical values for the test of Student amount to 1.96 at a 5 \% confidence level and to 1.64 at a 10 \% confidence level; 5 lags are considered for ARCH and LM tests.
Diagnostic tests show the presence of autocorrelation (LM tests) and heteroscedasticity (ARCH tests) in the residuals despite the HAC correction. The Jarque and Bera tests confirm the non-normality of the residuals. The RESET tests accept the specification of the models at a 5% confidence level.

Adjusted $R^2$ are relatively low in the error correction models. This result is not surprising since it is difficult to explain the variation of stock prices with macroeconomic fundamentals. Adjusted $R^2$ are more satisfying in the long run relationships since the models explain more than 90% of the variance of the (log of the) Eurostoxx and the S&P500.

The coefficients associated to the long run relationships are negative and significant. In other words, stock prices can wander away from their fundamental value in the short run, but they will converge towards their fundamental value in the long run.

The coefficients in the long run relationships are correctly signed: an increase in expected profits leads to an increase in stock prices as well as an increase in productivity. Conversely, an increase in oil prices and a downward sloping interest rate curve $((r_{t-1}^h - r_{t-1}^m) < 0$; meaning that investors expect a fall in economic activity$^{71}$) induce a decrease in stock prices.

We then convert the estimated fundamental real stock price index into a fundamental nominal stock price index with the following relationship:

$$\overline{sp_t} = \overline{sp_t}^r + p_t$$

We choose to smooth $\overline{sp_t}$ with a Hodrick-Prescott filter ($\lambda = 7200$ for the Eurostoxx and $\lambda = 50000$ for the S&P500) in order to isolate the permanent component of the stock price indices from their transitory component.

$^{71}$ Economic theory suggests that the interest rate spread forecasts future short-term interest rates. A negative interest rate spread forecasts both a recession and lower interest rates, while a sharply rising interest rate spread forecasts an economic expansion and higher interest rates.
For both the S&P500 and the Eurostoxx, the estimated fundamental stock prices represent the overappreciation of the stock market during the internet bubble (January 1998-December 2000) and the bubble induced by subprime assets (January 2007-December 2007). Estimations also represent the negative overreaction of the market at the burst of the respective bubbles. Indeed, US and European stock markets fall beyond their fundamental value before reaching their respective fundamental value.

I. Principle of the EM algorithm

The Expectation Maximization (EM) algorithm (Dempster, Laird and Rubin (1977)) is an iterative optimization method that allows finding the maximum likelihood of parameters in probabilistic models where the model depends on unobserved latent variables. The EM algorithm alternates between performing an expectation (E) step and a maximization (M) step.

In the E step, the missing parameters are estimated given the observed data and current estimates of the model parameters. The E step introduces a hidden variable $Z$ that makes the estimation of the likelihood function easier.

Let $X$, be a vector of random variables and $\theta$ be a vector of parameters. The objective is to find the maximum likelihood estimate of $\theta$. In other words, we wish to find $\theta$ in a set $\Omega$ such that $F(X, \theta)$ is a maximum. The likelihood function is described as a function of the vector of parameters $\theta$ given the data $X$: 
\[ L(X, \theta) = \ln F(X, \theta) = \sum_{i=1}^{N} \ln f(x_i, \theta) \]

Since \( \ln(x) \) is a strictly increasing function, the value of \( \theta \) that maximises \( F(X, \theta) \) also maximises \( \ln F(X, \theta) \). We define \( L(X, Z, \theta) \) such that:

\[ L(X, Z, \theta) = \ln F(X, Z, \theta) = \sum_{i=1}^{N} \ln f(z_i / x_i, \theta) + \sum_{i=1}^{N} f(z_i, \theta) \]

Hence:

\[ L(X, \theta) = L(X, Z, \theta) - \sum_{i=1}^{N} \ln f(z_i / x_i, \theta) \]

The \( E \) step computes an expectation of the log likelihood function with respect to the current estimate of the distribution for the latent variables. The \( E \) step can be interpreted as building a local lower-bound to the posterior distribution. This is achieved by using the conditional expectation conditional on the present value of \( \theta (\theta_k) \):

\[ E[L(X, \theta/ \theta_k)] = E[L(X, Z, \theta/ \theta_k)] = E[\sum_{i=1}^{N} \ln f(z_i / x_i, \theta) / \theta_k] \]

\[ \iff L(X, \theta, \theta_k) = Q(\theta, \theta_k) - H(\theta, \theta_k) \]

In the \( M \) step, the bound is optimised thus improving the estimate for the unknown parameters. The likelihood function is maximised under the assumption that the missing data are known. The \( M \) step computes the parameters which maximizes the expected log likelihood found in the \( E \) step. The next value of the vector of parameters \( \theta, \theta_{k+1} \) is chosen such that:

\[ L(X, \theta_{k+1}/\theta_k) \geq L(X, \theta_k/\theta_k) \quad \forall \theta \in \Omega \]

In other words, the \( M \) step chooses the parameters’ values \( \theta_{k+1} \) that maximises the quantity \( L(X, \theta_{k+1}/\theta_k) \) computed in the \( E \) step:

\[ M(\theta_{k+1}) = \arg \max_{\theta \in \Omega} \{ L(X, \theta_{k+1}/\theta_k) \} \]
The vector of parameters $\theta$ is then used to determine the distribution of the latent variables in the next $E$ step. The $E$ and $M$ steps are reiterated until the convergence of the algorithm. The convergence is achieved for the vector of parameters $\theta$ that provides the maximum value of the likelihood function. Convergence is ensured since the algorithm is guaranteed to increase the likelihood at each iteration.

The procedure of the EM algorithm can thus be summarised as follows. The vector of parameters $\theta$ is initialised: coefficients’ values based on the estimation of the state equations considered linearly allow defining the vector $\theta_0$. The two steps of the algorithm are then computed. Whenever the algorithm has not converged we reiterate the procedure.

The EM algorithm has the advantage to converge faster towards the optimal values of the log-likelihood function. However, the major drawback associated to the EM algorithm is that it can provide only local maximum likelihood. To counter this drawback we compute the EM algorithm based on different initial parameters’ values in order to increase the probability to reach the global maximum likelihood.

**J. Description of the algorithm used to estimate the heterogeneous agents model**

The general definition of a two-state Markov switching model is given by the following model:

$$
Y_t = \begin{cases} 
\alpha_{1,0} + \sum_{k=1}^{N} \alpha_{1,k}X_{1k,t} + \varepsilon_{1,t} & \text{if } S_t = 1 \\
\alpha_{2,0} + \sum_{k=1}^{N} \alpha_{2,k}X_{2k,t} + \varepsilon_{2,t} & \text{if } S_t = 2
\end{cases}
$$

The estimation of this model based on the EM algorithm implies several steps.

**Step 1**: We start by computing the density function conditional on each state $S_t$:

$$f(Y_t / S_t = i , I_{t-1} ; \theta) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp \left[ -\frac{(Y_t - \alpha_i ' X_{t})^2}{2\sigma_i^2} \right] \text{ with } i = 1, 2$$
Step 2: We compute the joint density function (or unconditional density function) equal to the product of the conditional density times the ergodic probability:

\[
\begin{align*}
\text{Unconditional Density} & \quad \text{Conditional Density} \quad \text{Ergodic Probability} \\
\frac{f(Y_t, S_t = i / I_{t-1} ; \theta)}{f(Y_t / S_t = i, I_{t-1}; \theta) \times P(S_t = i / I_{t-1} ; \theta)}
\end{align*}
\]

With \( P(S_t = i / I_{t-1} ; \theta) = \sum_{j=1}^{2} P(S_t = i, S_{t-1} = j / I_{t-1}, \theta) \) with \( i = 1, 2 \)

And \( P(S_t = i, S_{t-1} = j / I_{t-1}, \theta) = P(S_{t-1} = j) \times P(S_t = i / I_{t-1}; \theta) \) with \( i, j = 1, 2 \)

The probability \( P(S_{t-1} = j / I_{t-1}; \theta) \) is the transition probability found in the vector \( \theta \).

The probability \( P(S_t = i / I_{t-1}; \theta) \) is the filtered probability obtained in the iteration \( t-1 \).

To start the algorithm, the values of \( P(S_{t-1} = j / I_{t-1}; \theta) \) are required. We initially set \( P(S_{t-1} = j / I_{t-1}; \theta) = 0,95 \). Besides, \( P(S_t = j / I_{t-1}; \theta) = P(S_t = j / I_{t-1}, \theta) \) for \( j = 1,2; \) where \( P(S_t = j / I_{t}, \theta) \) are the ergodic probabilities set initially (at \( t = 0 \)) with the transition matrix. We have:

\[
P_0(S_t = 1 / I_1, \theta) = \frac{1 - P_0(S_t = 2 / S_{t-1} = 1)}{2 - P_0(S_t = 1 / S_{t-1} = 2) - P_0(S_t = 2 / S_{t-1} = 1)}
\]

And \( P_0(S_t = 2 / I_1, \theta) = \frac{1 - P_0(S_t = 1 / S_{t-1} = 2)}{2 - P_0(S_t = 1 / S_{t-1} = 2) - P_0(S_t = 2 / S_{t-1} = 1)} \)

Step 3: We compute the log-likelihood function by summing the joint density functions:

\[
L(Y, \theta) = \ln f(Y_t / I_{t-1} ; \theta) = \sum_{i=1}^{2} \ln f(Y_t, S_t = i / I_{t-1}; \theta)
\]
Step 4: The filtered probability is computed based on the conditional (Step 1) and unconditional (Step 2) density functions:

\[ P(S_t = i / I_t; \theta) = \frac{f(Y_t, S_t = i / I_{t-1}; \theta)}{f(Y_t / I_{t-1}; \theta)} \quad \text{with} \quad i = 1, 2 \]

We then iterate the four steps for \( t = t+1 \) to \( T \) (\( T \) = sample size) to get the full log-likelihood function of the model:

\[ L(Y, \theta) = \ln f(Y_t / I_{t-1}; \theta) \prod_{k=t+1}^{T} \ln f(Y_k / I_{k-1}; \theta) \]

Step 6: \( E \)-step of the EM algorithm:

The \( E \) step computes an expectation of the log likelihood function with respect to the current estimate of the distribution for the latent variables. The \( E \) step can be interpreted as building a local lower-bound to the posterior distribution. This is achieved by using the conditional expectation conditional on the present value of \( \theta \) (\( \theta_k \)):

\[ E[L(Y, \theta_k / \theta_k)] = E \left[ \ln f(Y_t / I_{t-1}; \theta_k) \prod_{k=t+1}^{T} \ln f(Y_k / I_{k-1}; \theta_0) \right] \]

Step 7: \( M \)-step of the EM algorithm:

In the \( M \) step, the bound is optimised thus improving the estimate for the unknown parameters. The \( M \) step computes the parameters which maximizes the expected log likelihood function found in the \( E \) step. The next value of the parameter \( \theta, \theta_{k+1} \) is chosen such that:

\[ L(Y, \theta_{k+1} / \theta_k) \geq L(Y, \theta_k / \theta_k) \]

The \( E \) and \( M \) steps are reiterated until the convergence of the algorithm. The convergence is achieved for the vector of parameters \( \theta \) that provides the maximum value of the likelihood function.

\[ M(\theta_{k+1}) = \arg \max_{\theta \in \Omega} \{ L(Y, \theta_{k+1} / \theta_k) \} \]
K. The uncovered equity return parity (URP)

Although URP was highlighted in Hau and Rey (2006), the seminal paper of Cappiello and De Santis (2005) introduces the concept of uncovered equity return parity (URP). URP is an arbitrage relationship between the foreign exchange market and stock markets. URP tells that the expected exchange rate variation \( \Delta s_t^e \) must be equal to the differential between the expected domestic and foreign stock returns \( (r_t - r_t^*) \):

\[
\Delta s_t^e = (r_t - r_t^*)
\]

With \( \Delta s_t^e \), the expected change in the exchange rate; \( r_t \), the expected return in the domestic stock market; \( r_t^* \), the expected return in the foreign stock market

Therefore, if stock returns in the domestic country are higher than in the foreign country, agents will expect a depreciation of the domestic currency. The depreciation of the domestic currency ensures that stock returns are equalised between the domestic and the foreign economies. URP thus guarantees equilibrium in international financial markets.

Cappiello and De Santis test URP from January 1991 to December 2003 with monthly data. Spot exchange rates include the synthetic euro until December 1998 and thereafter the actual euro, the Japanese Yen, the British pound, the Swiss franc, the Canadian dollar, the French franc and the Deutsche mark, all against the US dollar. Tests are based on the following equation:

\[
\Delta s_t^e = \alpha + \beta (r_t - r_t^*) + \epsilon_t
\]

Estimations based on GMM with HAC correction show that URP is verified for European currencies against the US dollar but not verified for the Japanese yen and the Canadian dollar. Besides, for the euro/dollar exchange rate, URP provides better out-of-sample forecasts than the naïve random walk model.
L. The implied volatility on option prices as an indicator of risk aversion

A lot of indicators can be used to measure risk aversion (Coudert and Gex (2007)). A common indicator used in the literature to proxy risk aversion in the market is the implied volatility on option prices. The main advantage of computing the implied volatility on option prices is that it reflects market expectations of future volatility and it thus provides a measure of fear among investors the market.

Implied volatility can be computed via the Black-Scholes (1973) model. Although there are a lot of pricing models available, the Black-Scholes (1973) model is the most commonly used formula to price option contracts. This model assumes that the price of the underlying asset follows a geometric Brownian motion (GBM):

\[ dS = \mu Sdt + \sigma Dw \]

With \( \mu Sdt \), the instantaneous expected drift rate

\( \sigma Dw \), the instantaneous variance rate

According to Itô’s lemma, the geometric Brownian motion implies that the price of the underlying asset will be lognormally distributed and its return will be normally distributed with constant mean and constant variance:

\[ \ln S_T \rightarrow \Phi[\ln S + (\mu - (1/2)\sigma^2)\tau, \sigma(\tau)^{1/2}] \]

\[ \ln S_T \rightarrow \Phi[\alpha, \beta] \]

This gives the following log-normal density function:

\[ q(S_T) = \frac{1}{S_T \beta \sqrt{2\pi}} \exp\left[-(\ln S_T - \alpha)^2 / 2 \beta^2 \right] \]
Black and Scholes (1973) show that the price of a European call option $C$ can be written as:

$$C(X, \tau) = S_T N(d_1) - \exp^{-r\tau} X N(d_2)$$

Where $N(x)$ is the cumulative probability density function for a standardised normal variable; $d_1 = \frac{\ln(S_T/X) + (r + (1/2) \sigma^2 \tau)}{\sigma \sqrt{\tau}}$; $d_2 = \frac{\ln(S_T/X) + (r - (1/2) \sigma^2 \tau)}{\sigma \sqrt{\tau}}$; $S_T$, the price of the underlying asset; $X$, the strike price; $r$, the risk-free interest rate during the option’s life; $\tau$, the option’s maturity or time to the expiration of the option ($\tau = T - t$); $T$, the maturity of the option; $\sigma$, the volatility of the underlying asset during the life of the option (that is, the standard deviation of the return on the underlying asset).

Therefore, the price of the option is a function of five variables $S$, $X$, $r$, $\tau$ and $\sigma$. The values of all variables are known except the value of the volatility $\sigma$. To be able to price an option, market participants must therefore estimate the future value of the volatility during the life of the option.

Estimating $\sigma$ necessitates assuming that the actual listed price of the call option is the correct price of the call option. Under this assumption, the only unknown variable in the Black-Scholes formula is $\sigma$. The value of $\sigma$ is estimated by rearranging the Black-Scholes formula such that $\sigma$ appears in the left-hand-side. This estimate of $\sigma$ is called the implied volatility.

Implied volatility is useful for investors since it reflects market expectations of future volatility. Given the fact that option prices are supposed to reveal the expectations of investors about future asset price dynamics, the measure of risk aversion as provided by the implied volatility on option prices can be viewed as a subjective measure of risk perception by agents in the market rather than an objective measure of risk aversion. However the literature seems to confuse the two concepts - risk aversion versus risk perception - and often considers risk perception as risk aversion.
Article 4

Conventions in the Foreign Exchange Market: Can they really explain Exchange Rate Dynamics?

Abstract

The present article provides an unorthodox model of exchange rate dynamics based on conventions that prevail among market agents. We build a theoretical model that highlights the mechanisms underlying the formation of market conventions. We then test this model empirically on the euro/dollar exchange rate between January 1995 and December 2008. We rely on two alternative methods: a macroeconomic analysis and an econometric analysis based on the estimation of a time-varying parameters model. Both methods show that market switches between fundamentals considered in a bull convention and in a bear convention explain the euro/dollar dynamics between January 1995 and December 2008. Besides, at horizons longer than 1 month, the out-of-sample forecasting power of the convention model beats the ones of the traditional exchange rate model and the random walk.

Keywords: Exchange Rate Dynamics, Convention Theory, Imperfect Knowledge Economics, Kalman filter, Genetic Algorithm
Résumé


Mots-Clés : Dynamique des Taux de Change, Théorie des Conventions, Imperfect Knowledge Economics, Filtre de Kalman, Algorithme Génétique
1. Introduction

The present paper provides an unorthodox way to model exchange rate dynamics based on conventions that prevail among market agents. The intuition behind the convention model is based on a stylised fact highlighted by De Grauwe (2000). De Grauwe argues that agents tend to look for fundamentals that confirm the observed movements in the exchange rate. For instance, economists attributed the large depreciation of the euro relative to the dollar between January 1999 and December 2002 to the strong growth performances in the United States relative to the euro zone. On the contrary, the appreciation of the euro relative to the dollar between December 2002 and December 2004 was justified by large current account deficits in the United States compared to the euro zone. Bachetta and van Wincoop (2005) theorised this idea in the scapegoat model. A fundamental variable is taken as a scapegoat to explain exchange rate dynamics in a given period of time. Our approach differs strongly from Bachetta and van Wincoop (2005). Our convention model borrows more elements from the Imperfect Knowledge Economics (IKE) approach pioneered by Frydman and Goldberg (2007).

We first build a theoretical model to explain the mechanisms underlying the formation of market conventions. The simulated exchange rate from the theoretical convention model replicates several stylised facts highlighted empirically in exchange rate dynamics. We then test this model empirically on the euro/dollar exchange rate. The period of analysis spans January 1995 to December 2008. We rely on two alternative methods. The first method is a macroeconomic analysis that aims at explaining the euro/dollar movements by relying on the consensus of economists. This method is based on the analysis of the fundamentals used by the economic and financial literature to justify the euro/dollar dynamics. The second method is based on an econometric approach. We estimate a time-varying parameters model to find the conventions that drive the euro/dollar dynamics.

Both methods show that market switches between fundamentals considered in a bull convention and in a bear convention explain the euro/dollar dynamics between January 1995 and December 2008. More precisely, the model shows that during the period of analysis, the market puts a large accent on the US and European productivity indices and dividend yields in times of optimism while a large weight is put on the US and European external debts, oil prices and US house prices in times of pessimism. The analysis underlines the existence of a non-linear relationship between fundamentals and the euro/dollar exchange rate. In other words, some fundamentals may be more important at some periods of time for the
determination of exchange rate dynamics while other fundamentals are important at other periods of time.

Both methods identify three major conventions in the euro/dollar market. The first convention is the new economy convention that covers the period January 1995 - December 2000. Investors are relatively more optimistic in the growth prospects of the US economy than in European economies. The dollar experiences a strong appreciating trend in this period. Between January 2001 and June 2003, the market relies on a bear convention based on the huge external debt of the US economy. The dollar starts a strong depreciating trend in this period. Then, between July 2003 and December 2005 two competing conventions prevail in the market. A bear convention that focuses mainly on the large US current account deficits; and a bull convention that points to the spectacular recovery of the US economy from the internet bubble burst. During this period the dollar alternates between short-lasting appreciating and depreciating trends according to whether the bull convention dominates the bear one. After January 2006, fundamentals worsen in the US economy. The bear convention starts to dominate the bull one. The spark of the subprime crisis in June 2007 definitely leads to the domination of the bear convention in the market.

The article compares the predictive performances of the convention model with regards to alternative models. Results show that at horizons longer than 1 month, the out-of-sample forecasting power of the convention model beats the ones of traditional models of exchange rate and the random walk.

The paper is organised as follows. Section 2 presents the main pillars of convention theory and proposes a theoretical model that defines the mechanisms underlying the formation of market conventions. Sections 3 and 4 find the possible conventions that prevail for the euro/dollar exchange rate among market agents between January 1995 and December 2008. Section 3 identifies the conventions by relying on a macroeconomic analysis while section 4 rests on an econometric approach based on the estimation of a time-varying parameters model. Section 4 tests the out-of-sample predictive power of the convention model relative to alternative specifications. Section 5 concludes.
2. Theoretical concepts

2.1 The main principles of convention theory

Convention theory has been developed by the pioneered work of Lewis (1969), Sugden (1989) and Peyton Young (1996). Convention theory comes as an alternative to the traditional theory of asset pricing. Traditional models of asset pricing are based on the efficient market hypothesis (EMH) and the rational expectations hypothesis (REH). Such models assume objectivity ex ante of the future and the existence of a unique intrinsic asset value (the fundamental value). In the tradition of the Arrow-Debreu model, the REH states that a representative agent can predict the future value of an asset by associating ex ante predetermined probabilities to exogenous future events. A rational agent can hence assess the fundamental value of an asset by computing the expected returns of the asset in each state of the Nature conditional on the disposable stock of information. According to the EMH, every asset price has a unique fundamental value that includes all the relevant information of the asset.

Models based on the EMH-REH paradigm offer poor empirical performances concerning the explanation and prediction of asset price dynamics, especially exchange rates (Meese and Rogoff (1983), Cheung, Chinn and Garcia Pascual (2005)). Such models led to unresolved asset pricing puzzles. Besides, assuming the existence of a unique fundamental value for an asset appears rather unrealistic. In a previous work, Bouveret and Di Filippo (2009) show that for the euro/dollar exchange rate, the market does not rely on a unique definition of the fundamental exchange rate but rather on a large panel of fundamental values. Each fundamental value belongs to a specific model designed by a particular agent. These facts cast doubts on the relevance of models based on traditional asset pricing theory.

Convention theory adopts a rather opposite view to traditional theory. Following Knight (1921) and Keynes (1936), convention theorists claim that the future is totally uncertain. No agent has the ability to know the probability distribution of future outcomes. The future is here shaped by the heterogeneity of opinions that agents frame on the fundamental value of an asset. There are as many fundamentals as there are opinions about the fundamental value of an asset. The future becomes hence subjective: each agent has his/her own opinion about the future value of the asset. All these opinions - translated into models of exchange rate determination - lead to the existence of multiple asset price equilibria in the market. The key question is how do these opinions converge towards a particular
equilibrium? Individual opinions converge towards a particular equilibrium through a mimetic mechanism. This mechanism was early illustrated by Keynes (1936) in his beauty contest. The primary objective for an agent in the market is to anticipate the reaction of the majority of participants in the market. As a matter of fact, if a market is bull on a given asset, an agent will have to buy the asset even if fundamentals tell him/her to sell the asset. This self-referential behaviour is rational at an individual level although it can lead to irrational phenomena (such as price bubbles) at a collective level. This self-referential behaviour consists in detecting striking events that could catch the attention of the majority of agents in the market. The choice of striking fundamentals is based on a trial-and-error strategy. Agents bet on the possible striking fundamentals that could catch the attention of the majority of agents in the market. Agents then build a model based on the selected fundamentals. The revisions of mistaken bets (or of bad models) imply an increasing volatility in asset prices. The market will stabilise itself when all agents - through mimetism - will focus on a particular striking set of fundamentals. At this point, agents have found a particular model based on a specific set of fundamentals. All agents in the market legitimate this model. This model is called a convention. A convention is therefore a fundamental model legitimated by all agents in the market, in a given time period. A convention therefore creates a focal point that helps resolving the problem of multiple asset price equilibria in the market. Once a convention is determined in the market, asset price volatility decreases. A convention therefore acts as a guide through the uncertainty covering the future dynamics of asset prices. Indeed agents can rely on the convention to form their expectations on the future value of the asset.

A convention can thus be defined as a particular fundamental model adopted by the majority of agents in a market concerning future economic prospects (Orléan (2006)). A convention often ignores other fundamentals that go against it. In order to live long enough, the asset price dynamics fitted by the convention has to match the actual dynamics of asset prices. However, market agents will not abandon a convention at the first anomalies i.e. when the empirical dynamics of asset prices go against the ones assumed by the convention. Agents will do so when there will be a series of events that are in opposition to the fitted exchange rate provided by the current convention. Agents’ beliefs in the current convention vanish and the convention disappears from the market. The uncertainty on the future dynamics of asset prices increases, and with it, exchange rate volatility. Market participants will then have to find a new convention.
2.2 A simple theoretical exchange rate model based on conventions

We set a simple theoretical model to explain the mechanisms underlying the formation of market conventions in the foreign exchange market. The model borrows elements from the Imperfect Knowledge Economics (IKE) approach by Frydman and Goldberg (2007).

We assume two countries (domestic and foreign) in an asymmetric world. The assumption of an asymmetric world implies that the influence of a given fundamental in the domestic and foreign countries does not have the same effect on exchange rate dynamics.

Following the IKE approach, the model considers two types of representative agents in the market: an optimistic (or bull) agent and a pessimistic (or bear) agent. The model is based on the following mechanism. When agents are relatively more optimistic in the domestic country than in the foreign country, they expect an appreciation of the domestic currency (and vice versa). Conversely, when agents are relatively more pessimistic in the domestic country than in the foreign country, they anticipate a depreciation of the domestic currency (and vice versa).

Agents are characterised by bounded rationality. Following a trial-and-error strategy, agents choose a bunch of fundamentals among the available set of fundamentals that best explain past exchange rate dynamics. We model the choice of fundamentals through a genetic algorithm.

The first step of the genetic algorithm is the initialization of the variables. We assume a set of 8 pairs of fundamentals split into two subsets.

\[
\Omega_{\text{Bull}} = \{(f_{1}, f_2^*), (f_3, f_4^*), (f_5, f_6^*), (f_7, f_8^*)\} \tag{1a}
\]

\[
\Omega_{\text{Bear}} = \{(f_9, f_{10}^*), (f_{11}, f_{12}^*), (f_{13}, f_{14}^*), (f_{15}, f_{16}^*)\} \tag{1b}
\]

The bull (bear) subset represents the stock of information used by optimistic (pessimistic) agents to forecast future exchange rate dynamics. As agents have bounded rationality, they rely on a particular stock of fundamentals to make their forecasts and ignore other fundamentals. In other words agents do not take account of the entire stock of information ($\Omega_{\text{Bull}}$ and $\Omega_{\text{Bear}}$) but rely instead on a particular subset of information to make their forecasts.
Agents are assumed to have knowledge of economic theory. In other words, they know the theoretical sign of the relationship between a given fundamental and the exchange rate. We assume that:

\[
\frac{ds_t}{df_{1,t}} > 0 ; \frac{ds_t}{df_{2,t}} < 0 ; \frac{ds_t}{df_{3,t}} > 0 ; \frac{ds_t}{df_{4,t}} < 0 ; \frac{ds_t}{df_{5,t}} > 0 ; \frac{ds_t}{df_{6,t}} < 0 ; \frac{ds_t}{df_{7,t}} > 0 ; \frac{ds_t}{df_{8,t}} < 0 \quad (2a)
\]

\[
\frac{ds_t}{df_{9,t}} < 0 ; \frac{ds_t}{df_{10,t}} > 0 ; \frac{ds_t}{df_{11,t}} < 0 ; \frac{ds_t}{df_{12,t}} > 0 ; \frac{ds_t}{df_{13,t}} < 0 ; \frac{ds_t}{df_{14,t}} > 0 ; \frac{ds_t}{df_{15,t}} < 0 ; \frac{ds_t}{df_{16,t}} > 0 \quad (2b)
\]

For example, if \( f_{1,t} \) and \( f_{2,t} \) are considered respectively as the domestic and foreign interest rates, then an increase in the interest rate differential in favour of the domestic economy (\( d(f_{1,t} - f_{2,t}) > 0 \)) will induce an appreciation of the domestic currency (\( ds_t > 0 \)). Also, if \( f_{9,t} \) and \( f_{10,t} \) are considered respectively as the domestic and foreign stocks of external debt, then an increase in the stock of domestic debt other things being equal (\( d(f_{9,t} - f_{10,t}) > 0 \)) leads the domestic currency to depreciate (\( ds_t < 0 \)).

Fundamentals are assumed to follow a random walk:

\[
f_{k,t} = f_{k,t-1} + \varepsilon_t^k
\]

Where \( \varepsilon_t^k \) mimics the impact of news on fundamentals \( \varepsilon_t^k \sim iidN(0,\sigma_{k,\varepsilon}^2) \)

The second step of the genetic algorithm is the selection of the variables. As agents cannot take account of all fundamentals due to bounded rationality, they select a limited bunch of fundamentals. We assume that in a given state, agents select two pairs of fundamentals among the four pairs available in the state. Thus, agents include four fundamentals (either from \( \Omega^{Bull} \); or from \( \Omega^{Bear} \)) in their model.

The selection of fundamentals that in turn creates a model of exchange rate determination is based on a fitness process. Agents first test the in-sample historical explanatory power of each possible model based on the above pairs of fundamentals. They then select the model (or the fundamentals) that best explain past exchange rate dynamics.

72 Indeed, this algorithm is very close to the building logic of market conventions.
Thus, each category of agents (optimistic or pessimistic) tests 6 possible models. We therefore end up with 12 models.

Bull agents test the following models (bull models are indexed from 1 to 6):

\[ s_i^k = \beta_{0,t} + \beta_{k,j} f_{k,t} - \beta_{k,j} f_{k+1,t} + \beta_{k,j} f_{k,t} - \beta_{k+1,j} f_{k+1,t} \quad \text{With } k \neq l \quad (4a) \]

Where \( k = 2a + 1 \) and \( l = 2a \) (\( a = 0 \) to \( 4 \)); \( i = 1 \) to \( 6 \); \( \beta_{0,t} \) is a constant

Bear agents test the following models (bear models are indexed from 7 to 12):

\[ s_i^j = \beta_{0,t} + \beta_{m,j} f_{m,t} - \beta_{m,j} f_{m+1,t} + \beta_{m,j} f_{m,t} - \beta_{m+1,j} f_{m+1,t} \quad \text{With } m \neq n \quad (4b) \]

Where \( m = 2b + 1 \) and \( n = 2b \) (\( b = 5 \) to \( 8 \)); \( j = 7 \) to \( 12 \); \( \beta_{0,t} \) is a constant

In order to assess the fitness of the above models, each agent estimates the models by ordinary least squares (OLS). The aim is to find the coefficients \( \hat{\beta} \) that minimize the sum of squared residuals of the model:

\[ \hat{\beta}^h = \arg \min_{\beta} \sum_{i=1}^{n} (s_i - x_{s,t}^h \beta)^2 \quad \text{With } h = 1 \text{ to } 12 \quad (5) \]

The estimated coefficients are given by:

\[ \hat{\beta}^h = \left( \frac{1}{n} \sum_{j=1}^{n} x_{s,j} x_{s,t}^h \right) \left( \frac{1}{n} \sum_{j=1}^{n} x_{s,j} s_i \right) \quad \text{With } h = 1 \text{ to } 12 \quad (6) \]

The fitted exchange rate is defined by:

\[ \hat{s}^h = \frac{1}{n} \sum_{j=1}^{n} x_{s,j} \left( \frac{1}{n} \sum_{j=1}^{n} x_{s,j} x_{s,t}^h \right) \left( \frac{1}{n} \sum_{j=1}^{n} x_{s,j} s_i \right) \quad \text{With } h = 1 \text{ to } 12 \quad (7) \]
Each agent computes the in-sample mean squared error (MSE) based on past exchange rate dynamics:

\[
MSE_i^h = \frac{1}{n} \sum_{t=h}^{n} (s_{t-h}^i - \hat{s}_{t-h})^2 \quad \text{With } h = 1 \text{ to } 12 \quad (8)
\]

The selected bull and bear models satisfy the following conditions:

\[
s_i^* = \text{Min}\{MSE_i^j\} \quad \text{With } i = 1 \text{ to } 6 \quad (9a)
\]

\[
s_i^* = \text{Min}\{MSE_i^j\} \quad \text{With } j = 7 \text{ to } 12 \quad (9b)
\]

The expected exchange rate from the model used by each agent is defined as:

\[
E_{o,t} (s_{t+1}^i) = \hat{\beta}_{0,t} + \hat{\beta}_{k,t} f_{k,t} - \hat{\beta}_{k+1,t} f_{k+1,t} + \hat{\beta}_{l,t} f_{l,t} - \hat{\beta}_{l+1,t} f_{l+1,t} \quad \text{With } i = 1 \text{ to } 6 \quad (10a)
\]

\[
E_{p,t} (s_{t+1}^j) = \hat{\beta}_{0,t} + \hat{\beta}_{m,t} f_{m,t} - \hat{\beta}_{m+1,t} f_{m+1,t} + \hat{\beta}_{n,t} f_{n,t} - \hat{\beta}_{n+1,t} f_{n+1,t} \quad \text{With } j = 7 \text{ to } 12 \quad (10b)
\]

The third step of the genetic algorithm is the reproduction of the best model. Agents drop the fundamental variables that do not explain well the past dynamics of exchange rates and look for the ones that provide a better fit of past exchange rate dynamics. In other words, agents re-iterate the procedure described above.

We assume that the proportion of optimistic and pessimistic agents in the market varies through time. We define the proportion of optimistic and pessimistic agents in the market as:

\[
\omega_{o,t} = \frac{\exp(\gamma \pi_{o,t}^i)}{[\exp(\gamma \pi_{o,t}^i) + \exp(\gamma \pi_{p,t}^i)]} \quad \text{and} \quad \omega_{p,t} = \frac{\exp(\gamma \pi_{p,t}^i)}{[\exp(\gamma \pi_{o,t}^i) + \exp(\gamma \pi_{p,t}^i)]} \quad (11)
\]

Where \( \omega_{o,t} + \omega_{p,t} = 1 \) and \( 0 < \gamma < 1 \)
The parameter $\gamma$ represents the intensity at which agents revise their forecasting rules. Usually, we set $\gamma$ close to zero and away from unity since as underlined in section 2.1, a convention does not disappear at the first anomalies between the fitted asset price dynamics by the convention and the actual asset price dynamics.

The profitability $\pi'_{i,t}$ of each rule is evaluated according to the profit $\pi_{i,t}$ and the risk $\sigma^2_{i,t}$ related to this rule:

$$\pi'_{i,t} = \pi_{i,t} - \mu \sigma^2_{i,t} \quad i = o, p \quad (12)$$

The parameter $\mu$ represents the coefficient of risk aversion. The risk associated to a forecasting rule is defined as the variance of the forecasting error:

$$\sigma^2_{i,t} = [E_{i,t}(s_i) - s_i]^2 \quad i = o, p \quad (13)$$

The profit $\pi_{i,t}$ related to a forecasting strategy is defined as the one-period earnings of investing one unit of domestic currency in the foreign asset:

$$\pi_{i,t} = [s_i(1 + r^*) - s_{t-1}(1 + r)] \text{sgn}[E_{i,t}(s_i)(1 + r^*) - s_{t-1}(1 + r)] \quad i = o, p \quad (14)$$

Where

$$\text{sgn}[x] = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x = 0 \\ -1 & \text{if } x < 0 \end{cases}$$

We obtain the expected exchange rate at time $t+1$ by aggregating agents’ forecasts in the market:

$$E_t(\Delta s_{t+1}) = \omega_o E_{o,t}(\Delta s_{t+1}) + \omega_p E_{p,t}(\Delta s_{t+1}) \quad (15)$$

Hence:

$$\Delta s_{t+1}^{\text{Market}} = \omega_o \Delta s_{t+1}^{\text{bull}} + \omega_p \Delta s_{t+1}^{\text{bear}} + \epsilon_{t+1} \quad (16)$$
Figure 1.1 shows the simulations’ results of the theoretical convention model for 1000 periods (we assume $\mu = 5$ and $\gamma = 0.2$). The blue margins mean that the market is in majority optimistic ($P(S_t=Bull/I_t) > 0.5$) while the white margins mean that the market is globally pessimistic ($P(S_t=Bull/I_t) < 0.5$).

**Figure 1.1: Simulated exchange rate dynamics and probability to be in the bull state**

NB: The black line represents the market exchange rate (left scale); the blue line represents the probability to be in the bull state (right scale); the orange line represents the Hodrick-Prescott filter ($\lambda = 14400$) of the probability to be in the bull state (right scale).

Figure 1.1 shows that the simulated exchange rate alternates between periods of appreciating and depreciating trends. Also, the proportion of bull and bear agents in the market varies through time.

In this model, agents go through two selection processes that define two switching mechanisms.

The first selection process (equations (1a) to (10b)) is the selection of the best model by bull and bear agents. This choice is based on the relative performances of the past explanatory powers of exchange rate models based on fundamentals coming respectively from the bull and bear information stocks. Through time, bull and bear agents switch between their respective models and choose the model that provides the best explanatory power of past exchange rate dynamics. Figure 1.2 represents the models chosen by optimistic and pessimistic agents through time.
Figure 1.2: Model chosen by optimistic agents (models 1 to 6) and pessimistic agents (models 7 to 12)

Figure 1.2 shows that between $t = 1$ and $t = 300$ optimistic agents alternate between models 1, 2 and 3. Over the same period, pessimistic agents rely on model 12. Thus in this period, model 12 provides the best explanatory power of past exchange rate dynamics given the stock of fundamentals used by bear agents. Taking a backward view, the convention model implies that there is not a unique fundamental model of exchange rate in the market but a variety of fundamental models of exchange rate in which agents rely on to determine the fundamental value of the exchange rate.

The second selection process (equations (11) to (14)) is the choice of whether being bull or bear in the market. This choice depends on the relative profitability of the selected bull model relative to the selected bear model. Through time, agents can switch between being a bull or a bear agent given the profitability of the model selected by bull and bear agents.

Figure 1.3 represents the relative profitability of being bull in the market ($\pi'_{o,t} - \pi'_{p,t}$). The green area means that the selected bull model generates a positive profitability relative to the selected bear model. Conversely, the red area means that being bull is less profitable than being bear.
Figure 1.3 shows that when the selected model by bull agents generates a positive profitability relatively to the selected bear model, bull agents dominate the market. On the contrary, when the selected model by bull agents generates a negative profitability relatively to the selected bear model, bear agents become dominant in the market.

Figure 1.4 shows the relative weights put by agents on domestic and foreign fundamentals for model 1, model 2, model 8 and model 12. The relative weights are computed as the contributions of the coefficients for the estimated models in the bull state ($\Omega^{\text{Bull Model} 1}$) and in the bear state ($\Omega^{\text{Bear Model} 1}$). For example, in the case of model 1, we have:

$$
\Omega^{\text{Bull Model} 1} = \frac{\hat{\beta}_1 f_1 + \hat{\beta}_3 f_3}{\hat{\beta}_1 f_1 + \hat{\beta}_2 f_2 + \hat{\beta}_3 f_3 + \hat{\beta}_4 f_4} ; \quad \Omega^{\text{Bear Model} 1} = \frac{\hat{\beta}_1 f_1 + \hat{\beta}_3 f_3}{\hat{\beta}_1 f_1 + \hat{\beta}_2 f_2 + \hat{\beta}_3 f_3 + \hat{\beta}_4 f_4}
$$

(17)

Figure 1.4 shows that the weights agents attribute to domestic and foreign fundamentals vary through time. In some periods, agents put a larger weight on domestic fundamentals relative to foreign fundamentals while at other periods, agents put a lower weight on domestic fundamentals relative to foreign fundamentals.
The paragraph below provides a key understanding of the results from figures 1.1, 1.2, 1.3 and 1.4. We have here four cases in the market.

First, in figure 1.1, an appreciation (a depreciation) of the domestic (foreign) currency in the bull state means that agents are relatively more optimistic in the domestic economy than in the foreign economy. For example, in figure 1.1, from $t = 70$ to 100, the market is bull ($P(S_t=Bull|I_t) > 0.5$) and the domestic currency appreciates. Agents are in majority bull because being bull is more profitable than being bear (figure 1.3). Optimistic agents rely on model 1 in this period (figure 1.2) and put more weight on domestic fundamentals than on foreign fundamentals (figure 1.4.1).

Secondly, in figure 1.1, an appreciation (a depreciation) of the foreign (domestic) currency in the bull state means that agents are relatively more optimistic in the foreign economy than in the domestic economy. For instance, in figure 1.1, from $t = 450$ to 525, the market is bull and the domestic currency depreciates. Figure 1.3 shows that over the period the profitability of being bull is higher than the one of being bear. The best model selected by bull agents in this period is model 2 (figure 1.2). Based on model 2, bull agents put more weight on foreign fundamentals than on domestic fundamentals (figure 1.4.2).

Thirdly, in figure 1.1, a depreciation (an appreciation) of the domestic (foreign) currency in the bear state means that agents are relatively more pessimistic in the domestic
economy than in the foreign economy. As a matter of facts, from $t = 580$ to $620$ in figure 1.1, the market is bear ($P(S_t=Bull/I_t) < 0.5$) and the domestic currency depreciates over the period. The profitability of being bear is higher than the one of being bull (figure 1.3). The selected model by bear agents is model 8 (figure 1.2). Model 8 puts more weight on domestic fundamentals than on foreign fundamentals (figure 1.4.3).

Fourthly, in figure 1.1, a depreciation (an appreciation) of the foreign (domestic) currency in the bear state means that agents are relatively more pessimistic in the foreign economy than in the domestic economy. For instance, we observe in figure 1 from $t = 150$ to $200$ that the market is bear and that the domestic currency appreciates. Being bear is indeed more profitable than being bull in this period (figure 1.3). The model chosen by bear agents is model 12 (figure 1.2). Model 12 puts a lower weight on domestic fundamentals than on foreign fundamentals (figure 1.4.4).

Finally, the theoretical convention model shows that exchange rate dynamics are driven by the time-varying fundamental models or equivalently by convention models selected by market agents through time.

The convention model offers several advantages compared to recent models of exchange rate such as the heterogeneous agents models (De Grauwe and Grimaldi (2007)). Heterogeneous agents models explain exchange rates dynamics based on the behaviour of fundamentalist and chartist agents. Such models fully predetermine the behaviour of economic agents by associating an exogenous rule to each agent. Agents therefore act as robots in these models. On the contrary, the convention model follows the IKE approach by partially predetermining the behaviour of agents. Indeed, agents can use whatever rules or investment strategies. Such rules are allowed to evolve over time based on a trial-and-error strategy. Moreover, the convention model does not rely on the controversial definition of a fundamental exchange rate. On the contrary, heterogeneous agents models have to specify an arbitrary value for the fundamental exchange rate in the fundamentalist rule.

Having highlighted the mechanisms behind the formation of market conventions, we now test the theory of conventions in the foreign exchange market. The asset of interest is the euro/dollar exchange rate. The period of analysis runs from January 1995 to December 2008.

We rely on two methods to identify the fundamentals considered in conventions by market agents. The first method is a macroeconomic analysis. This method analyses the weight given to a particular macroeconomic fundamental by the economic and financial
literature in a given period of time. Results are presented in section 3. The second method relies on the estimation of a time-varying parameters model. This method computes the time-varying dynamics of the coefficients’ value associated to a particular fundamental through time. Results are presented in section 4.

3. A macroeconomic analysis of market conventions

This section highlights the conventions that prevail in the euro/dollar market by relying on a macroeconomic analysis. The aim is to rely on the consensus of the market concerning the fundamentals that best explain the euro/dollar exchange rate dynamics. We rely on major articles from financial journals (Wall Street Journal and The Economist) as well as academic ones. We justify each argument by using figures from Thomson Datastream and from the Bureau of Economic Analysis. The results of this analysis are organised in the following five sections.

3.1 January 1995 - December 2000: the internet convention or the superiority of the US economy compared to the euro zone

In the second half of the 1990s, the US economy experienced a stronger growth rate than Europe (an average of 8.3 % for the United States versus 5 % for Europe (figure 1)). Stronger growth in the United States was attributed to larger investments in new technologies compared to Europe. Such investments helped increase the productivity differential in favour of the United States (figure 2). In December 2008, the differential in productivity growth rates amounted to 3 %. Numerous economists praised the glorious prospects offered by the US economy. Some economists (of whom Jeremy Rifkin) even claimed that the US economy had reached a higher structural growth rate. The market was clearly in presence of a convention defining the US economy as more profitable than the European economy.

73 For figures 1 to 23, data come from Thomson Datastream; and from the Bureau of Economic Analysis concerning capitals flows (figures 3, 7 and 21).
Financial investors therefore expected higher returns in US stocks than in European stocks. They invested massively in US stocks, especially in companies belonging to the sector of the new economy (the ever-known start-ups). Net equity flows in the United States increased by an average of 24 % a year between 1998 and 2000 (figure 3). The annual average growth rate of the S&P500 between January 1995 and December 2000 amounted to 21 % a year (figure 23).

The birth of the euro zone in 1999 and the youth of the European Central Bank (ECB) - which had to set its credibility among market agents - led investors to be more timorous in the European economy than in the US economy.
Therefore, between January 1995 and December 2000, markets were relatively more optimistic on the prospects of the US economy relative to the ones of the European economy. The bull sentiment that prevailed in the market was referred to as the new economy convention or the internet convention.

### 3.2 January 2001-June 2003: the burst of the internet bubble and the end of the new economy convention

The over-optimistic sentiment in the US economy led to a bubble in stock prices: the internet bubble. This bubble burst in January 2001. This shock put an end to the new economy convention. Investors realised that their expectations on the prospects of the US economy were too optimistic.

Financial papers began to put the accent on variables hidden during the internet convention. The stronger US growth rate was gauged on a growing debt in the public and private sectors. US companies over-estimated the future demand and faced higher debt and excess capacities. The high level of US consumption had rested on an increasing debt allowed by the positive wealth effect induced by the rise in stock prices during the inflating phase of the internet bubble.

The increase in public and private debts induced mechanically an increase in the deficit of the current account balance (figure 6) and induced the return of the twin deficits. A lot of economists began to ask about the sustainability of US deficits (Mann (2002)) and a possible fall in the dollar.

To counter the economic slowdown induced by the internet bubble burst, the Federal Reserve decreased dramatically its main interest rate. The interest rate differential became now in favour of the European economy (figure 5).
Investors became thus relatively less confident in the US economy than in the European economy. They reduced investments in stocks and foreign direct investment (FDI) in the United States. Between January 2001 and June 2003, the S&P500 lost 44 % and the Eurostoxx 60 %. The financial scandals of Enron and Worldcom and then the attacks of the 11th September 2001 kept increasing the bear sentiment on the US economy. Equity flows in the United States decreased (figure 7) and the dollar stopped its appreciating trend begun earlier in January 1995 (figure 8). The dollar started to depreciate in June 2002. This depreciation was however contained by interventions of East-Asian central banks. Indeed, East-Asian central banks bought US bonds to prevent a severe appreciation of their currency against the dollar.

The bear sentiment of investors on the US economy does not mean that investors became bull in the European economy. Indeed, the excess in the current balance experienced by the euro zone at that period (figure 6) suggests that the growth rate has been very low and was still very low in the euro zone during this period.
As a result, between January 2001 and June 2003, financial markets faced an increase in uncertainty concerning economic recovery either in the euro zone or in the United States. Deflation fears induced by lower growth rates prevailed among economists and central bankers. The market definitely abandoned the internet convention. Agents became bear either in the United States and or in the euro zone. The bear sentiment was however relatively stronger in the United States than in the euro zone.

3.3 July 2003-December 2005: The birth of two competing conventions: the US consumption as the engine of the world economy versus the US as a net debtor

From July 2003, fears of deflation induced by the bubble burst vanished. The US economy was recovering surprisingly fast from the burst of the internet bubble (figure 9). Factors behind the US recovery were the large decrease of interest rates by the Federal Reserve (figure 10) coupled with an increase in public spending (through the decrease in taxes under the Bush government and the increase in military spending (related to wars in Iraq and in Afghanistan)).

Conversely, the euro area was dealing with a weaker growth rate. Economists started to ask about the relevance of the institutional structure of the euro zone. They began to blame the Growth and Stability Pact because this pact could prevent the euro area from higher growth rates. Members of the euro zone seemed unable to lead a relevant fiscal policy to counter the economic slowdown. Between July 2003 and December 2005 the annual growth rate reached 1,7 % in the euro zone compared to 4,8 % in the United States (figure 9). Lower
interest rates associated to surging house prices (figure 13) allowed US households to ease their access on credit and to increase their consumption. At that time, financial papers argued that the US consumption was the engine of the world economy.

However, several factors seemed to limit investors’ confidence in the US economy. Indeed, the US consumption was gauged on a higher level of debt for US households. Besides, the return of growth in the United States generated no increase in US employment. As shown in figure 11, the growth rate of US employment was close to the one in the euro zone although the growth differential was strongly in favour of the United States (figure 9). This fact was partly explained by relocations of US firms to China. Such relocations led the US economy to increase imports of Chinese goods which contributed to the increase of the US deficit (figure 12). In 2005, the US current deficit reached 6% of GDP.

All these factors can explain why the dollar still depreciates even after the recovery of the US economy between July 2003 and December 2004.
At the beginning of 2004, higher growth in the US and increasing oil prices led the Federal Reserve to increase its main interest rate (figure 10). The interest rate differential became in favour of the US economy in December 2004.

Finally, between July 2003 and December 2005, two competing conventions appeared in the market. A first convention (bear convention) focused mainly on large US current deficits and expected a fall in the dollar. A second convention (bull convention) pointed to the fast recovery of the US economy after the bubble burst and its good resistance with regards to the increase in oil prices (figure 14). The bull sentiment was also attributed to the success of the fine monetary policy by Alan Greenspan, chairman of the Federal Reserve at that time. The domination of the bear convention may explain the depreciation of the dollar between July 2003 and December 2004. Conversely, the domination of the bull convention may explain the appreciation of the dollar between January 2005 and December 2005.

3.4 January 2006 - June 2007: the weakening of the bull convention

Between January 2006 and June 2007, the bull sentiment associated to the resistance and the high potential of the US economy became more and more threatened by several negative news about the US economy.

Indeed, the sustained growth in the United States between July 2003 and December 2005 was gauged on a positive growth rate of house prices. Between January 2006 and September 2007, the growth rate of US house prices decreased (figure 13). Economists began to warn about a possible burst of a bubble in US house prices.
On the other hand, oil prices were surging and acted as a burden on the budget of US households. The barrel of Brent reached 96.05 $ in November 2007 (figure 14). Investors feared a decrease in US households’ consumption either by the decrease in house prices that could reduce or even close access to credit for US households or by the increase in oil prices that would reduce the disposable income of US households. Fears were also accentuated by the increase in the main interest rate by the Federal Reserve (figure 18) which raised the burden of debt for US households.

![Figure 13: US house prices (annual growth rate)](image)

![Figure 14: Oil price dynamics (Brent)](image)

NB: For Figure 13 and 14, the solid black line represents the euro/dollar nominal exchange rate.

Negative news about the US economy were also illustrated by the worrying concerns about the sustainability of the US debt. US current deficits were evaluated at more than 6 % of US GDP in 2006 and at about 5.5 % of US GDP in 2007 (figure 15). Fears increased among investors about a possible fall in the dollar and hence in the value of assets denominated in dollars. Threats by Chinese authorities to convert part of their huge stock of accumulated dollars (figure 16) in another currency accentuated fears by investors about a possible dollar fall.
The rising bear sentiment in the US economy led investors to be relatively more optimistic about the prospects of the euro zone. Investors became aware that the US economy had not significantly outperformed the European economy in the recent years. Growth in the euro area was at its fastest pace since January 2002 and the growth differential between the United States and the euro zone became very thin from January 2007 to December 2007 (figure 17). In 2007, inflation fears related to the increase in oil prices led the ECB to increase its main interest rate. At the end of 2007, the interest rate differential became in favour of the euro zone (figure 18).

In December 2007, investors became uncertain about the prospects offered by the US economy. Economists and central bankers began questioning whether the US economy would experience a soft-landing or a hard-landing. The bull convention that appeared between July 2003 and December 2005 in the United States was fading out at an increasing pace. The
increasing domination of the bear convention may explain why the dollar depreciates between January 2006 and December 2007.

3.5 June 2007 - December 2008: the subprime crisis and the end of the bull convention in the US economy

The bankruptcy of two investment funds of Bear Stearns in June 2007 sparked a major financial crisis in the United States. In spring 2007, the Federal Reserve along with the ECB intervened massively in the interbank market to prevent a liquidity crisis.

The Federal Reserve began to decrease its main interest rate in June 2007 (figure 20) while the ECB kept its rates unchanged because of inflation fears caused by increasing oil prices and also because growth forecasts were still more optimistic in the euro zone than in the United States (figure 19).

In October 2007, the bubble on US house prices burst (figure 13). Investors faced a great uncertainty about the future prospects of the US economy. Nobody really knew how bad the subprime crisis would have hurt the US economy. Support brought by the Federal Reserve and the ECB to bad banks in the second half of 2007 prevented both economies from a large financial crisis. However, concerns were now surging about a possible contagion of the financial turmoil to the real economy. Economists feared especially a credit crunch triggered by unhealthy banks that invested in subprime assets. A credit crunch would indeed end access of US households to credit, hence stopping US consumption; one of the main components that sustained US growth until then.

In April 2008 growing evidence raised that the US economy was in recession. Conversely, the European economy seemed at a first time less affected by the financial crisis. Figure 22 shows that European employment still raised when unemployment in the United States increased. Newspapers pointed to the relative resistance of European economies although the growth rate in the euro zone lowered. With oil prices still surging and preventing the ECB to decrease its main interest rate, economists feared the return of stagflation in the Euro area as well as in the United States.
The growth rate in the United States became negative and US unemployment surged in August 2008 (figures 19 and 22). Later, in November 2008, the Euro zone experienced a negative GDP growth rate (figure 19). The ECB started to decrease its main interest rate in December 2008 (figure 20).

A bear sentiment prevailed among financial markets concerning the economic prospects either in the euro zone or in the United States. Stock indices started to fall in October 2008. Investors became more averse to risky assets. Net flows of equities in the United States became negative in 2008 (figure 21) and US investors retrieved their liquidities from the euro area. This outflow of capitals from the euro zone partly explains the depreciation of the euro vis-à-vis the dollar between July 2008 and November 2008 (figure 19).
From September 2008 until June 2009 the US and European governments were beginning to set plans to put an end to the financial crisis and to counter the economic recession. However, market agents cast doubts on the relevance of the successive plans proposed by both governments (especially the US government). In May 2009, some economists feared a W shaped recession such as in the 1939 financial crisis. From the peak of June 2007 to the trough of March 2009, the S&P500 fell by 50 % (figure 23). Over the same period, the Eurostoxx fell by 57 %.

NB: The dashed grey line refers to the euro zone; the solid grey line refers to the United States and the solid black line represents the euro/dollar nominal exchange rate.
3.6 Conventions highlighted by the macroeconomic analysis

The above analysis allows distinguishing 5 phases and three main conventions for the euro/dollar exchange rate between January 1995 and December 2008.

The new economy convention prevailed from January 1995 to December 2000. Investors were relatively more optimistic on the prospects of the US economy than on the ones of the European economy. Investors were fascinated by stronger US growth rates and higher expected profits offered by the US economy. The dollar experiences a strong appreciating trend during this period. In January 2001, the burst of the internet bubble put an end to the new economy convention.

Between January 2001 and June 2003, investors were bear either in the United States or in the euro zone. The market was looking for a new convention. The market started to build a bear convention based on the high external deficits of the US economy. The dollar starts a strong depreciating trend in this period.

From July 2003 to December 2005 two competing conventions prevailed among market participants. A bear convention focused mainly on large US current deficits and a bull convention pointed notably to the spectacular recovery of the US economy from the internet bubble burst. During this period the dollar stops its strong depreciating trend and alternates between short-lasting appreciating and depreciating trends according to whether the bull convention dominates the bear one.

Between January 2006 and June 2007, the bear convention started to dominate the bull one. Indeed, several factors came against the bull convention notably the possible burst of the US house price bubble that could trigger an economic downturn in the United States and the surge in oil prices that acted as a burden on US households’ disposable income.

In June 2007, the subprime crisis put an end to the bull convention. Investors became bear in the United States as well as in the Euro zone. The bear convention definitely dominates the market at that time.

The next step of the analysis aims at testing the degree of relevance of the conventions highlighted by the macroeconomic analysis. We rely on an econometric approach based on the estimation of a time-varying parameters model.
4. An econometric analysis of market conventions

To test the significance of the results highlighted in the macroeconomic analysis we define an alternative and more objective approach. We use econometric tools and estimate a time-varying parameters model. The aim is to identify the most important fundamentals among all the fundamentals considered in the macroeconomic analysis. We compute the time-varying dynamics of the coefficients’ value associated to macroeconomic fundamentals through time. To give credit to the econometric approach, we build a research procedure close to the theoretical convention model presented in section 2. The research procedure follows three steps. The first step identifies the most important fundamentals in the determination of the euro/dollar exchange rate. The second step builds all the models that can be built with the selected fundamentals. The third step analyses the predictive power of each model and selects the model that offers the best predictions for the euro/dollar exchange rate dynamics.

4.1 Analysis of the time-varying weight of macroeconomic fundamentals

The quest for the most important fundamentals in the determination of the euro/dollar exchange rate is based on the estimation of a time-varying parameters model. We use a state-space model estimated with a Kalman filter. The state-space model allows us to find the variables that have the highest weight (i.e. the highest coefficient) in the determination of the euro/dollar exchange rate through the period of analysis.

The measurement equation includes all the fundamentals considered in the macroeconomic analysis (section 3). We consider the following fundamentals: the industrial production (\textit{indprod}); the productivity (\textit{pdty}); the net investment position over GDP (\textit{niipgdp}); the number of employed people (\textit{employ}); the price of oil (\textit{op}); the house price index (\textit{hpi}); the stock price index (\textit{sp}); the expected profits on the related stock indices (\textit{expprofit}); the dividend yield on the related stock indices (\textit{divyield}); the short run (3-months) interest rate (\textit{stinrate}); the long run (10-years) interest rate (\textit{lgintrate}). These fundamentals are the ones considered by the literature concerning the determination of the euro/dollar exchange rate at a monthly frequency (Camarero \textit{et al.} (2005), Bouveret and Di Filippo (2009)).

State-space models are composed by two equations: a measurement equation that describes the relation between observed variables (exogenous fundamentals) and unobserved state variables; and a state equation (or transition equation) that defines the dynamics of the state variables.
The measurement equation takes the following form:

\[
s_t = \alpha_{0,t} + \alpha_{1,t} \text{indprod}_{t}^{SU} + \alpha_{2,t} \text{indprod}_{t}^{EU} + \alpha_{3,t} \text{pdy}_{t}^{SU} + \alpha_{4,t} \text{pdy}_{t}^{EU} + \alpha_{5,t} \text{niipgdp}_{t}^{SU} + \alpha_{6,0} \text{niipgdp}_{t}^{EU} + \alpha_{7,t} \text{employ}_{t}^{EU} + \alpha_{8,t} \text{employ}_{t}^{SU} + \alpha_{9,t} \text{sp}_{t}^{SU} + \alpha_{10,t} \text{sp}_{t}^{EU} + \alpha_{11,t} \text{hpi}_{t}^{SU} + \alpha_{12,t} \text{hpi}_{t}^{EU} + \alpha_{13,t} \text{exp profit}_{t}^{EU} + \alpha_{14,t} \text{exp profit}_{t}^{SU} + \alpha_{15,t} \text{divyield}_{t}^{EU} + \alpha_{16,t} \text{divyield}_{t}^{SU} + \alpha_{17,t} \text{st int rate}_{t}^{EU} + \alpha_{18,t} \text{st int rate}_{t}^{SU} + \alpha_{19,t} \text{lg int rate}_{t}^{EU} + \alpha_{20,t} \text{lg int rate}_{t}^{SU} + \epsilon_t
\]  

(18)

We assume that the coefficients in the state equations follow a random walk:

\[
\alpha_{i,t} = \alpha_{i,t-1} + \epsilon_{i,t} \quad \text{with } i = 0 \text{ to } 21
\]  

(19)

Table 1 shows the estimation output for the coefficients over the period January 1995-December 2008. The fundamental variables are classified by the importance of their coefficient value.74

Table 1: Estimation output of the time-varying parameters model

<table>
<thead>
<tr>
<th>Variables</th>
<th>niipgdpUS</th>
<th>niipgdpEU</th>
<th>divyieldUS</th>
<th>divyieldEU</th>
<th>sintrateUS</th>
<th>sintrateEU</th>
<th>pdtyEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>1,13</td>
<td>[2,19]</td>
<td>0,98</td>
<td>0,97</td>
<td>0,97</td>
<td>0,96</td>
<td>0,94</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables</th>
<th>lgintrateEU</th>
<th>lgintrateUS</th>
<th>pdyUS</th>
<th>spUS</th>
<th>speU</th>
<th>hpiUS</th>
<th>op</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>0,94</td>
<td>[0,08]</td>
<td>0,93</td>
<td>0,89</td>
<td>0,88</td>
<td>0,83</td>
<td>0,78</td>
</tr>
<tr>
<td></td>
<td>[6,43]</td>
<td>[3,12]</td>
<td>[1,99]</td>
<td>[2,33]</td>
<td>[2,64]</td>
<td>[4,01]</td>
<td>[6,80]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables</th>
<th>employUS</th>
<th>expprofitUS</th>
<th>indprodUS</th>
<th>employEU</th>
<th>indprodEU</th>
<th>expprofitEU</th>
<th>chineseres</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>0,57</td>
<td>[0,08]</td>
<td>0,57</td>
<td>0,49</td>
<td>0,44</td>
<td>0,42</td>
<td>0,35</td>
</tr>
<tr>
<td></td>
<td>[4,70]</td>
<td>[1,29]</td>
<td>[0,25]</td>
<td>[3,15]</td>
<td>[4,96]</td>
<td>[0,14]</td>
<td></td>
</tr>
</tbody>
</table>

Table 1 shows that in majority, US fundamentals have larger coefficients than European fundamentals. Thus, news coming from the United States have a larger impact on the euro/dollar exchange rate than news coming from the euro zone. This result has been found in earlier studies that analyse the effect of news on the euro/dollar exchange rate (Prast...)

74 Other results relative to the state-space model such as the classification of the fundamentals through time are available upon author request.
and De Vor (2000), Galati and Ho (2001) and Andersen et al. (2003)). The fact that investors react asymmetrically to news on a given fundamental between two countries justifies the assumption of an asymmetric world in the convention model.

The selection of the fundamentals to be included in the convention model obeys to the following procedure. We consider only the dominant fundamentals i.e. the fundamentals that have the largest coefficients. Fundamentals characterised by the lowest coefficients i.e. dominated fundamentals are rejected. Also, for sake of parsimony, we drop the dominated fundamentals that are correlated to dominant variables or that cover the same information set as dominant variables. For example, in table 1 the dividend yields divyield have larger coefficients relative to expected profits expprofit and to stock indices sp. As these variables cover the same information set - information relative to the stock market - we consider only the dividend yield in the convention model. Also, the productivity pdty (defined as the gross domestic product over the number of employed people) has a higher coefficient than the industrial production indprod and the number of employed people employ. As these variables are highly correlated among each other we only select the variable pdty.

Besides, we do not select either the short run or the long run interest rates. Indeed the short and long run interest rates differentials between the United States and the euro zone are too low over the estimation period to explain the dynamics of the euro/dollar exchange rate.

Following this selection procedure, we end up with the following main fundamentals for the determination of the euro/dollar dynamics in the sample period: the net external position over GDP (netiipgdp), the productivity (pdty), the dividend yield (divyield), the US house price (hpi) and the price of oil (op).

The next step is to build all the possible fundamental models that can be built based on the selected fundamentals. We will then keep the models that offer the best predictive power of the euro/dollar exchange rate dynamics.

4.2 Analysis of the predictive performances of the fundamental models

We test the predictive power of all the possible models that can be built with the fundamentals selected with the time-varying parameters model. In line with the theoretical convention model exposed in section 2, we include the respective couples of domestic and foreign fundamentals in the models. We thus end up with 6 possible convention models (table 2, column 2). We analyse the performance of the one month out-of-sample recursive
Recursive forecasts\textsuperscript{75}. For example, for model 1, the one-month out-of-sample exchange rate forecast is given by:

\[ s_{t+1}^{\text{Model1}} = \alpha_0 + \beta_1 \text{pdty}_{t}^{\text{EU}} + \beta_2 \text{pdty}_{t}^{\text{US}} + \beta_3 \text{divyield}_{t}^{\text{EU}} + \beta_4 \text{divyield}_{t}^{\text{US}} + \epsilon_{t+1} \]

The predictive performance is assessed based on three statistics: the root mean squared error (\textit{RMSE}), the mean average error (\textit{MAE}) and the prediction of the direction of change (\textit{DoC}). Models are estimated in-sample from January 1995 to December 1995 based on monthly data. The out-of-sample period runs from January 1996 to December 2008. Forecast statistics of the different models are shown in table 2.

**Table 2: Predictive power of the fundamental models**

<table>
<thead>
<tr>
<th>No</th>
<th>Models</th>
<th>\textit{RMSE}</th>
<th>\textit{MAE}</th>
<th>\textit{DoC}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>\textit{s} = {\text{pdtye}, \text{pdtyu}, \text{divyielde}, \text{divyields}}</td>
<td>0.0883</td>
<td>0.0666</td>
<td>0.5714</td>
</tr>
<tr>
<td>2</td>
<td>\textit{s} = {\text{pdtye}, \text{pdtyu}, \text{niipgdpe}, \text{niipgdps}}</td>
<td>0.0641</td>
<td>0.0514</td>
<td>0.4870</td>
</tr>
<tr>
<td>3</td>
<td>\textit{s} = {\text{divyielde}, \text{divyields}, \text{niipgdpe}, \text{niipgdps}}</td>
<td>0.0785</td>
<td>0.0600</td>
<td>0.5195</td>
</tr>
<tr>
<td>4</td>
<td>\textit{s} = {\text{divyielde}, \text{divyields}, \text{op}, \text{hpius}}</td>
<td>0.0826</td>
<td>0.0572</td>
<td>0.5714</td>
</tr>
<tr>
<td>5</td>
<td>\textit{s} = {\text{niipgdpe}, \text{niipgdps}, \text{op}, \text{hpius}}</td>
<td>0.0916</td>
<td>0.0675</td>
<td>0.5844</td>
</tr>
<tr>
<td>6</td>
<td>\textit{s} = {\text{niipgdpe}, \text{niipgdps}, \text{op}, \text{hpius}}</td>
<td>0.0720</td>
<td>0.0578</td>
<td>0.6039</td>
</tr>
</tbody>
</table>

NB: \textit{RMSE} stands for the root mean squared error; \textit{MAE} stands for the mean average error; \textit{DoC} stands for the direction of change.

Table 2 shows a lot of heterogeneity in the predictive performances of the models. For instance, model 2 has the lowest mean average error but only predicts the right direction of change of the euro/dollar exchange rate in 48.70 \% of cases. Also, model 6 provides the highest performance in terms of the prediction of the direction of change. However model 6 has a lower performance relative to other models when predicting the value of the exchange rate (\textit{RMSE} and \textit{MAE}). Table 3 classifies the models according to their respective statistics.

**Table 3: Classification of the fundamental models**

<table>
<thead>
<tr>
<th>Statistics</th>
<th>\textit{RMSE}</th>
<th>\textit{MAE}</th>
<th>\textit{DoC}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model Classification</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 2</td>
<td>Model 2</td>
<td>Model 6</td>
<td></td>
</tr>
<tr>
<td>Model 3</td>
<td>Model 4</td>
<td>Model 5</td>
<td></td>
</tr>
<tr>
<td>Model 6</td>
<td>Model 6</td>
<td>Model 1 and Model 4</td>
<td></td>
</tr>
</tbody>
</table>

NB: \textit{RMSE} stands for the root mean squared errors; \textit{MAE} stands for the mean average errors; \textit{DoC} stands for the direction of change.

\textsuperscript{75} Recursive forecasts aim at estimating the model in-sample for a given period of time and forecasting the endogenous variable out-of-sample. We then estimate the model by adding one observation to the previous in-
Table 3 indicates that model 2 offers the best predictions of the future value of the exchange rate (RMSE and MAE) but performs poorly in the prediction of the direction of change of the euro/dollar exchange rate (DoC). Considering all statistics, model 6 appears as the best classified model relative to the other models.

As our theoretical model assumes that convention models do not share the same fundamentals, the other selected model has to be model 1. Indeed, model 1 shares a different set of fundamentals compared to model 6.

Therefore, we end up with two fundamental models or two convention models:

\[ s_{t, \text{Model} 1} = \alpha_0 + \alpha_1 pt_{t, EU} + \alpha_2 pt_{t, US} + \alpha_3 divyeld_{t, EU} + \alpha_4 divyeld_{t, US} + \varepsilon_t \]  \hspace{1cm} (20)

\[ s_{t, \text{Model} 6} = \beta_0 + \beta_1 niipgd_{t, EU} + \beta_2 niipgd_{t, US} + \beta_3 op_{t} + \beta_4 HP_{t, US} + \eta_t \]  \hspace{1cm} (21)

Because market conventions are models used by agents in a given period of time, they can be econometrically interpreted as long term relationships between the exchange rate and the fundamentals considered in the conventions. We therefore test whether the selected convention models (equations (20) and (21)) have a significant long run relationship with the euro/dollar exchange rate. We follow the method of Engle and Granger (1987). We estimate both models based on an error correction mechanism (ECM):

\[ \Delta s_{t, \text{Model} 1} = \beta_1 \Delta pt_{t, EU} + \beta_2 \Delta pt_{t, US} + \beta_3 \Delta divyeld_{t, EU} + \beta_4 \Delta divyeld_{t, US} + \lambda \left[ s_{t-1} - \alpha_0 - \alpha_1 pt_{t-1, EU} - \alpha_2 pt_{t-1, US} - \alpha_3 divyeld_{t-1, EU} - \alpha_4 divyeld_{t-1, US} \right] + \varepsilon_t \]  \hspace{1cm} (22)

\[ \Delta s_{t, \text{Model} 6} = \beta_1 \Delta niipgd_{t, EU} + \beta_2 \Delta niipgd_{t, US} + \beta_3 \Delta op_{t} + \Delta HP_{t, US} + \lambda \left[ s_{t-1} - \alpha_0 - \alpha_1 niipgd_{t-1, EU} - \alpha_2 niipgd_{t-1, US} - \alpha_3 op_{t-1} - \alpha_4 HP_{t-1, US} \right] + \varepsilon_t \]  \hspace{1cm} (23)

The estimation period runs from January 1995 to December 2008. As all variables are stationary in the ECM (see appendices B and C), the estimation method is based on ordinary least squares (OLS). We take account of the eventual presence of heteroskedasticity and autocorrelation in the residuals by applying the HAC correction of Newey-West (1987). Table 4 shows the estimation output.
Table 4: Estimation output of the error correction models

<table>
<thead>
<tr>
<th>Models</th>
<th>$\lambda$</th>
<th>$\alpha_0$</th>
<th>$\alpha_1$</th>
<th>$\alpha_2$</th>
<th>$\alpha_3$</th>
<th>$\alpha_4$</th>
<th>R²adj</th>
<th>R²adj L.T</th>
<th>ARCH</th>
<th>LM</th>
<th>J&amp;B</th>
<th>RESET Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>-0.07 [-3.13]</td>
<td>3.19</td>
<td>-1.33</td>
<td>0.53</td>
<td>-0.18</td>
<td>0.49</td>
<td>0.13</td>
<td>0.78</td>
<td>3.73 (0.02)</td>
<td>14.84 (0.00)</td>
<td>4.28 (0.11)</td>
<td>0.48 (0.48)</td>
</tr>
<tr>
<td>Model 6</td>
<td>-0.041 [-2.74]</td>
<td>1.80</td>
<td>-0.15</td>
<td>0.05</td>
<td>0.02</td>
<td>-0.06</td>
<td>0.08</td>
<td>0.87</td>
<td>3.41 (0.03)</td>
<td>12.29 (0.00)</td>
<td>1.11 (0.57)</td>
<td>1.50 (0.22)</td>
</tr>
</tbody>
</table>

NB: Student statistics are mentioned in square brackets; p-values are mentioned in brackets; critical values for the test of Student amount to 1.96 at a 5% confidence level and to 1.64 at a 10% confidence level; 5 lags are considered for ARCH and LM tests.

Diagnostic tests show that although there is heteroskedasticity and autocorrelation in the residuals for models 1 and 6 (in spite of the HAC correction), RESET tests do not reject the specification of the selected models.

Adjusted $R^2$ associated to the error correction models are rather weak (lower than 15%). This result, often found in the literature (Camarero et al. (2005), Bouveret and Di Filippo (2009)), is related to the difficulty of explaining exchange rate returns based on macroeconomic fundamentals. Conversely, adjusted $R^2$ associated to the long run relationships are more satisfying since both models explain at least 78% of the variance of the euro/dollar exchange rate.

For both models, the coefficients $\lambda$ are significant and negative. This result validates the existence of a significant long run relationship between the exchange rate and fundamentals considered in model 1 and in model 6. This fact justifies the persistence of the selected convention models through time.

However, the coefficients in the long run relationship are not correctly signed. Subperiods tests for both models indicate large changes in the coefficients’ value. This instability in the coefficients’ value - often found in the literature - is justified by the high instability in the empirical link between a given fundamental and the exchange rate. Also, the asymmetric structure considered in models 1 and 6 fosters the presence of multicollinearity between the exogenous variables i.e. the fundamental variables. Multicollinearity is another factor that is likely to explain the instability in the coefficients’ value associated to macroeconomic fundamentals.

76 Results are available upon author request.
4.3 Lessons from the convention model: can conventions explain the euro/dollar dynamics?

We present in figure 24 the dynamics of the euro/dollar exchange rate as well as the respective errors of the long term relationships of the selected convention models (model 1 (equation (20)) and model 6 (equation (21)); with:

\[ \varepsilon_t = s_t - \hat{s}_{t}^{\text{Model1}} \]  \hspace{1cm} (24)

\[ \eta_t = s_t - \hat{s}_{t}^{\text{Model6}} \]  \hspace{1cm} (25)

The blue margins indicate the periods where errors from models 1 are lower than errors from model 6. Thus in the blue margins model 1 provides a better explanatory power of the euro/dollar dynamics than model 6 (and vice versa for the white margins).

Figure 24: Euro/dollar dynamics and time-varying explanatory powers of the convention models

NB: the bold black line represents the dynamics of the euro/dollar exchange rate (right scale); the grey line represents the errors relative to model 6 (left scale); the black line represents the errors relative to model 1 (left scale); the blue margins represent the periods in which errors from model 1 are lower than errors from model 6.

Figure 24 shows that the relative explanatory power of model 1 and model 6 varies through time. More precisely, one can observe that model 1 dominates in the explanation of the euro/dollar exchange rate in periods of optimism (i.e. in bull periods; blue margins in
figure 24) while model 6 dominates in the explanation of the euro/dollar exchange rate in periods of pessimism (i.e. in bear periods; white margins in figure 24).

Indeed, from January 1995 to December 2000, model 1 provides on majority the best explanatory power relative to model 6. During this period, investors were globally optimistic. The internet convention prevailed at that time. Investors were optimistic about the future growth prospects and the returns (or dividend yields) offered by the US and the European stock markets. The dollar has a strong appreciating trend during this period.

We notice however that the explanatory power of model 6 is higher between September 1997 and March 1999. This observation is related to the Asian crisis of 1997 and then the Russian crisis of 1998 that causes financial turmoil in the US financial markets through the quasi-bankruptcy of the Long Term Capital Management (LTCM) fund.

The burst of the internet bubble in January 2001 led to the collapse of the new economy convention. This convention suddenly disappeared from the market. The market became more pessimistic about the prospects of both the US economy and the European economy. Between January 2001 and January 2003, the fundamentals considered in model 6 offer the best explanatory power. As mentioned in the macroeconomic analysis, the market was at that time concerned by the large external debt of the US economy - a fundamental variable found in model 6. The dollar starts a strong depreciating trend in this period.

From February 2003 to December 2005, the US economy recovers from the internet bubble burst. However, investors were still concerned about the increasing external debt of the US economy. During this period, the best explanatory power of the euro/dollar exchange rate dynamics is offered alternatively by model 1 and model 6. As a result, the market alternates between two convention models. On the one hand, there are agents who believe in a bull convention (model 1) based on the resistance of the US economy, its fast recovery from the internet bubble burst and the induced returns (dividend yields) offered by the US economy. On the other hand, there are agents who believe in a bear convention (model 6) related to concerns about the sustainability of the large US debt. During this period the dollar stops its strong depreciating trend and alternates between short-lasting appreciating and depreciating trends according to whether the bull convention dominates the bear one.

From January 2006 until December 2008, model 6 provides in the majority of times, the best explanatory power of the euro/dollar exchange rate. The accumulation of negative news concerning the US economy after January 2006 (larger US current account deficits, increasing fears about a possible burst of the US house price bubble, surge in oil prices) puts an end to the bull convention (model 1) shared by agents in the previous period. The start of
the subprime crisis in June 2007 definitely led to the domination of the bear convention (model 6) in the market. The dollar starts a significant depreciating trend in this period.

The analysis of the econometric results shows that the euro/dollar market alternates between bull and bear periods. Model 1 provides a high explanatory power in periods of optimism while model 6 offers a high explanatory power in periods of pessimism. Therefore, model 1 and model 6 can be considered respectively as a bull convention and as a bear convention. Globally, the convention model explains the euro/dollar dynamics by the switches between fundamentals considered in the bull and in the bear conventions. More precisely, the market puts a large accent on the US and European productivity indices and dividend yields in times of optimism while in times of pessimism the market puts a large weight on the US and European external debt, oil prices and US house prices. This result provides evidence of the existence of a non-linear relationship between fundamentals and the euro/dollar dynamics. In other words, some fundamentals are important at some periods of time in the determination of exchange rate dynamics but less important at other periods of time.

The econometric analysis ends up with the same results as the macroeconomic analysis. Indeed, as in the macroeconomic analysis, the econometric analysis highlights five phases and three main conventions for the euro/dollar exchange rate between January 1995 and December 2008: a bull convention based on the new economy between January 1995 and December 2000 (with a bear subperiod between September 1997 and March 1999 due to the contagion effects of the Asian crisis); a bear convention based on the large US external debt, the fears about a possible house price bubble burst and the negative effect of the increase in oil prices on the US economy between January 2001 and December 2008; and a bull convention based on the spectacular recovery of the US economy from the stock market crash caused by the collapse of the internet convention (February 2003-December 2005). The econometric analysis thus validates empirically the macroeconomic analysis of market conventions. It validates also the theoretical model of conventions. As a result, the euro/dollar dynamics may be driven by market conventions i.e. by time-varying fundamental models.
4.4 Assessing the predictive power of the convention model

We compare the predictive performances of the convention model with regards to four alternative models. The considered models are defined below:

- Model 1 assumes a linear structure and a symmetric world. Model 1 thus represents traditional models of exchange rate:

\[
\Delta_{t+k}^{\text{Model1}} = \alpha_0 + \alpha_1 (pdy_{t}^{EU} - pdy_{t}^{US}) + \alpha_2 (divyield_{t}^{EU} - divyield_{t}^{US}) \\
+ \alpha_3 (niipgdp_{t}^{EU} - niipgdp_{t}^{US}) + \alpha_4 op_{t} + \alpha_5 HPI_{t}^{US} + \varepsilon_{t+k}
\]  

(26)

- Model 2 rests on a linear structure and an asymmetric world. By assuming an asymmetric world, the structure of model 2 is more realistic than the one of model 1:

\[
\Delta_{t+k}^{\text{Model2}} = \alpha_0 + \alpha_1 pdy_{t}^{EU} + \alpha_2 pdy_{t}^{US} + \alpha_3 divyield_{t}^{EU} + \alpha_4 divyield_{t}^{US} \\
+ \alpha_5 niipgdp_{t}^{EU} + \alpha_6 niipgdp_{t}^{US} + \alpha_7 op_{t} + \alpha_8 HPI_{t}^{US} + \varepsilon_{t+k}
\]  

(27)

- Model 3 relies on a non-linear structure and an asymmetric world. Model 3 is the convention model. Model 3 assumes that the dynamics between exchange rates and their fundamentals are nonlinear and asymmetric:

\[
\Delta_{t+k}^{\text{Model3}} = \begin{cases}
\alpha_0 + \alpha_1 pdy_{t}^{EU} + \alpha_2 pdy_{t}^{US} + \alpha_3 divyield_{t}^{EU} + \alpha_4 divyield_{t}^{US} + \varepsilon_{t+k} & \text{if } \varepsilon_i < \eta_i \\
\beta_0 + \beta_1 niipgdp_{t}^{EU} + \beta_2 niipgdp_{t}^{US} + \beta_3 op_{t} + \beta_4 HPI_{t}^{US} + \varepsilon_{t+k} & \text{if } \varepsilon_i > \eta_i
\end{cases}
\]  

(28)

- Model 4 is the simple random random walk without drift:

\[
\Delta_{t+k}^{\text{Model4}} = s_t + \varepsilon_{t+k} \quad \text{Where } \varepsilon_{t+k} \sim iidN(0, \sigma^2)
\]  

(29)

We first estimate in-sample the four models from January 1995 to December 1999. We then forecast out-of-sample the exchange rate of our respective models between January 2000 and December 2008. We use recursive forecasts based on OLS methods. Forecast

\[\text{Recursive forecasts aim at estimating the model in-sample for a given period of time and forecasting the endogenous variable out-of-sample. We then estimate the model by adding one observation to the previous in-}\]
horizons are 1 month, 3 months, 6 months, 1 year, 2 years and 5 years. Table 5 shows the forecast errors of the models.

Table 5: Comparative forecast performances between the convention model and alternative specifications

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Horizon</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 month</td>
<td>3 months</td>
<td>6 months</td>
<td>1 year</td>
<td>2 years</td>
</tr>
<tr>
<td>RMSE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1</td>
<td>0.0569</td>
<td>0.0590</td>
<td>0.0591</td>
<td>0.0614</td>
<td>0.0672</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.0565</td>
<td>0.0601</td>
<td>0.0603</td>
<td>0.0650</td>
<td>0.0827</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.0573</td>
<td>0.0581</td>
<td>0.0576</td>
<td>0.0585</td>
<td>0.0607</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.0306</td>
<td>0.2651</td>
<td>0.3511</td>
<td>0.4748</td>
<td>0.6216</td>
</tr>
<tr>
<td>MAE</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1</td>
<td>0.0378</td>
<td>0.0416</td>
<td>0.0416</td>
<td>0.0452</td>
<td>0.0532</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.0372</td>
<td>0.0435</td>
<td>0.0428</td>
<td>0.0478</td>
<td>0.0587</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.0386</td>
<td>0.0399</td>
<td>0.0389</td>
<td>0.0406</td>
<td>0.0442</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.0235</td>
<td>0.1126</td>
<td>0.1690</td>
<td>0.2838</td>
<td>0.4558</td>
</tr>
<tr>
<td>DoC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1</td>
<td>0.4481</td>
<td>0.4675</td>
<td>0.4740</td>
<td>0.3896</td>
<td>0.3442</td>
</tr>
<tr>
<td>Model 2</td>
<td>0.3961</td>
<td>0.4610</td>
<td>0.4286</td>
<td>0.4026</td>
<td>0.3961</td>
</tr>
<tr>
<td>Model 3</td>
<td>0.3052</td>
<td>0.3506</td>
<td>0.3506</td>
<td>0.2662</td>
<td>0.2403</td>
</tr>
<tr>
<td>Model 4</td>
<td>0.6111</td>
<td>0.5648</td>
<td>0.5185</td>
<td>0.4815</td>
<td>0.3704</td>
</tr>
</tbody>
</table>

NB: RMSE stands for root mean squared errors; MAE stands for mean absolute errors; DoC stands for the average percentage of right directions in the forecasts of future prices.

Table 5 shows that for short run horizons i.e. at 1 month, the random walk beats all the fundamental models. As long as the horizon increases - from 3 months to 5 years - fundamental models start to beat the random walk in term of exchange rate value forecasts (RMSE and MAE). The convention model (model 3) provides the best out-of-sample exchange rate value forecasts from 3 months to 5 years. The convention model provides however unsatisfying results concerning direction forecasts (DoC). Indeed, the random walk provides the best out-of-sample direction forecasts from 1 month until 1 year. This result is probably due to the momentum effect peculiar to the exchange rate dynamics at short/medium run horizons. As long as the horizon extends, the momentum effect becomes weaker. Indeed, between 2 years and 5 years, model 2 provides the best out-of-sample direction forecasts. We notice also that the traditional model of exchange rate (model 1) provides the worst forecasts whatever horizon considered. Therefore, table 5 proves that to improve exchange rate forecasts one can rely on a model that assumes a nonlinear and asymmetric structure i.e. a structure close to the empirical stylised facts observed in exchange rate dynamics. Indeed, the best predictions of future exchange rates values based on fundamental variables are offered by model 3 - the convention model (nonlinear and asymmetric structure). Traditional models of
exchange rate (linear and symmetric structure) offer the worst forecasts in the period of analysis.

5. Conclusion

This paper provides an unorthodox way to model exchange rate dynamics based on conventions that prevail among market agents. The paper presents a theoretical model that describes the formation of conventions by agents in the market. The structure of the theoretical model borrows elements from the Imperfect Knowledge Economics approach by Frydman and Goldberg (2007). The simulated exchange rate from the theoretical convention model replicates several stylised facts highlighted empirically in exchange rate dynamics. We test empirically the theoretical model on the euro/dollar exchange rate between January 1995 and December 2008. In a first step, we make use of a macroeconomic analysis to highlight the conventions that prevail on the euro/dollar exchange rate. In a second step, we build an econometric approach to find market conventions. We use a time-varying parameters model to find the most important fundamentals in the determination of the euro/dollar exchange rate. The macroeconomic analysis and the econometric approach end up with the same conclusions. Both analyses show that the market tends to switch between periods of optimism and periods of pessimism. Moreover, switches between fundamentals associated to a bull convention and to a bear convention explain the dynamics of the euro/dollar exchange rate. Finally, we show that the convention model offers the best exchange rate forecasts at horizons longer than 1 month relative to traditional models of exchange rate and to the random walk.

As the convention model offers promising results in the explanation and the prediction of the euro/dollar exchange rate dynamics, it could be interesting to extend the convention model to other exchange rates or even to other assets in order to assess the robustness of convention theory. As a matter of facts, Schulmeister (2009) shows that asset price dynamics in the foreign exchange market, stock markets and commodity markets exhibit the same patterns. All three markets tend to alternate between bull and bear periods.
References


Knight Frank H., 1921, “Risk, Uncertainty and Profit”, Boston: Houghton Mifflin


Appendices

A. Variables considered in the convention model

The period of analysis spans January 1995 to December 2008 on a monthly frequency. Data come from the following sources: Thomson Datastream and US Federal Housing Finance Agency.

Table A: Description of the series

<table>
<thead>
<tr>
<th>Type of Variable</th>
<th>Name</th>
<th>Model Name</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Endogenous</td>
<td>euro/dollar exchange rate</td>
<td>( s_t )</td>
<td>Datastream</td>
</tr>
<tr>
<td>Exogenous</td>
<td>productivity</td>
<td>( pdty_t )</td>
<td>Datastream</td>
</tr>
<tr>
<td>Exogenous</td>
<td>dividend yield</td>
<td>( divyield_t )</td>
<td>Datastream</td>
</tr>
<tr>
<td>Exogenous</td>
<td>net external investment position</td>
<td>( niipgdp_t )</td>
<td>Datastream</td>
</tr>
<tr>
<td>Exogenous</td>
<td>oil prices (North Sea Brent)</td>
<td>( op_t )</td>
<td>Datastream</td>
</tr>
<tr>
<td>Exogenous</td>
<td>US house prices</td>
<td>( HPI_t )</td>
<td>US Federal Housing Finance Agency</td>
</tr>
</tbody>
</table>

NB: We do not consider the European house price index since house prices did not experience a bubble (only perhaps in the Spanish economy negligible at a European level).

A.1 Endogenous variable: the euro/dollar exchange rate

The endogenous variable is the variation in the (log of the) nominal exchange rate \( s_t \):

\[
\Delta s_t = \log(S_t/S_{t-1})
\]

With \( S \), the euro/dollar nominal exchange rate (listed as 1 euro per \( S \) dollars).

A.2 Exogenous variables

- The industrial production (INDPROD) which plays the role of a proxy for GDP:

\[
\Delta indprod_t = \log(INDPROD_t/INDPROD_{t-1})
\]

With \( INDPROD \), the monthly index of industrial production. This series is available in monthly frequency.
- The expected profits ($PROFIT^a$):

$$
\Delta profit_t^a = \log\left( \frac{PROFIT_t^a}{PROFIT_{t-1}^a} \right)
$$

With $PROFIT_t^a$, internal profits, with $PER_t$ the price earning ratio related to the respective stock indices. This series is available in monthly frequency.

- The external debt ($NIIPGDP$):

$$
\Delta niipgdp_t = NIIPGDP_t - NIIPGDP_{t-1}
$$

With $NIIPGDP$, the net international position over the GDP of the respective economic zones. These variables are available only at an annual frequency. The series were transformed in a monthly frequency through a Quadratic Match Average filter. For the building of the ECM model, we smoothed this series with a Hodrick-Prescott filter (we considered $\lambda=14400$).

- Oil prices ($OP$):

$$
\Delta op_t = \log\left(\frac{OP_t}{OP_{t-1}}\right)
$$

With $OP$, the oil price as listed for the barrel of Brent of the North Sea. This series is available in monthly frequency.

- House prices in the United States ($HPI$).

$$
\Delta HPI_t = \log\left(\frac{HPI_t}{HPI_{t-1}}\right)
$$

With $HPI$, the house price index IAS360 delivered by the US Federal Housing Finance Agency (formerly OFHEO). This series is available in monthly frequency.
A.3 Remarks

Concerning the euro zone, when data is not available before 1999, we compute an artificial euro zone composed by a weighted average of GDP in Germany ($GDP_t^1$), France ($GDP_t^2$) and Italy ($GDP_t^3$). Thus for the unavailable data $x_t$ before 1999, we compute them as:

$$x_t = \frac{GDP_t^1}{\sum_{i=1}^{3} GDP_t^i} x_t^1 + \frac{GDP_t^2}{\sum_{i=1}^{3} GDP_t^i} x_t^2 + \frac{GDP_t^3}{\sum_{i=1}^{3} GDP_t^i} x_t^3$$

For the external debt, we rely partly on data by Lane and Milesi-Ferretti (2007). For sake of precisions, we compare the computed series with variables computed for the Area Wide Model of the euro zone (Fagan, Henry and Mestre (2001)).

B. Stationarity tests for the error correction models

Stationarity tests are based on three tests: the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Results are presented in tables B.1 and B.2.

Table B.1: Stationarity tests for the endogenous variable of the convention model

<table>
<thead>
<tr>
<th>Variables</th>
<th>$ADF$</th>
<th>$PP$</th>
<th>$KPSS$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta s$</td>
<td>-8.91*** (0.00)</td>
<td>-9.67*** (0.00)</td>
<td>0.09*</td>
</tr>
</tbody>
</table>

NB: For the ADF test the Akaike criteria with 2 lags is considered; $p$-values are mentioned in brackets; stars denote a stationary series at a 1 % (***) , 5 % (**), 10 %(*) confidence level.

Table B.2: Stationarity tests for the exogenous variables of the convention model

<table>
<thead>
<tr>
<th>Variables</th>
<th>$ADF$</th>
<th>$PP$</th>
<th>$KPSS$</th>
<th>Variables</th>
<th>$ADF$</th>
<th>$PP$</th>
<th>$KPSS$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta pty_{EU}$</td>
<td>-2.59 (0.28)</td>
<td>-6.75*** (0.00)</td>
<td>0.08*</td>
<td>$\Delta niipgdp_{EU}$</td>
<td>-5.33*** (0.00)</td>
<td>-47.43*** (0.00)</td>
<td>0.12</td>
</tr>
<tr>
<td>$\Delta pty_{US}$</td>
<td>-3.39** (0.05)</td>
<td>-6.75*** (0.00)</td>
<td>0.07**</td>
<td>$\Delta niipgdp_{US}$</td>
<td>-4.34*** (0.00)</td>
<td>-33.97*** (0.00)</td>
<td>0.12</td>
</tr>
<tr>
<td>$\Delta divyield_{EU}$</td>
<td>-10.75*** (0.00)</td>
<td>-55.18*** (0.00)</td>
<td>0.12</td>
<td>$\Delta op$</td>
<td>-9.73*** (0.00)</td>
<td>-9.82*** (0.00)</td>
<td>0.08**</td>
</tr>
<tr>
<td>$\Delta divyield_{US}$</td>
<td>-9.73*** (0.00)</td>
<td>-84.37*** (0.00)</td>
<td>0.21***</td>
<td>$\Delta HPI$</td>
<td>-12.93*** (0.00)</td>
<td>-5.42*** (0.00)</td>
<td>0.31</td>
</tr>
</tbody>
</table>

NB: For the ADF test, the Akaike criteria with 2 lags is considered; $p$-values are mentioned in brackets; stars denote a stationary series at a 1 % (***) , 5 % (**), 10 %(*) confidence level.
Stationarity tests validate the stationarity of the series considered in the fundamental models.

C. Estimation procedure for the ECM model

The estimation procedure of the ECM models follows three steps. The first step checks whether all series have the same order of integration. Table C.1 shows that all series are integrated of order one.

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_t^{EC}$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>$pdby_t^{EC}$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>$pdby_t^{US}$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>divyield$_t^{EU}$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>divyield$_t^{US}$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>niipgdp$_t^{EU}$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>niipgdp$_t^{US}$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>op$_t$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
<tr>
<td>HPI$_t^{US}$</td>
<td>I(1)</td>
<td>I(1)</td>
<td>I(1)</td>
</tr>
</tbody>
</table>

In a second step, we look for the number of cointegrated vectors by applying Trace tests and Maximum Eigenvalue tests. Results available in table C.2 (column 4) validate the presence of at most one cointegrated vector between the exchange rate and its fundamentals. We therefore estimate a univariate error correction model.

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data Trend</td>
<td>None</td>
</tr>
<tr>
<td>Type de Test</td>
<td>No Intercept</td>
</tr>
<tr>
<td>No Trend</td>
<td>No Trend</td>
</tr>
<tr>
<td>Trace</td>
<td>2</td>
</tr>
<tr>
<td>Max-Eigenvalue</td>
<td>1</td>
</tr>
</tbody>
</table>

| Data Trend | None | None | Linear | Linear | Quadratic |
| Type de Test | No Intercept | No Intercept | Intercept | Intercept | Intercept |
| No Trend | No Trend | No Trend | No Trend | No Trend | No Trend |
| Trace | 5 | 3 | 1 | 1 | 0 |
| Max-Eigenvalue | 2 | 2 | 1 | 1 | 1 |

NB: Critical values are based on the tables of MacKinnon, Haug and Michelis (1999).
In a third step, we estimate the long run relationships by ordinary least squares (OLS). The long-run relationships are defined as follows:

\[ s^{\text{Model1}}_t = \alpha_0 + \alpha_1 p_{dt}{^E}^{U} + \alpha_2 p_{dt}{^U}^{E} + \alpha_3 \text{divyield}{^E}^{U} + \alpha_4 \text{divyield}{^U}^{E} + \epsilon_t \]

\[ s^{\text{Model6}}_t = \beta_0 + \beta_1 \text{niipgdp}_{^E}^{U} + \beta_2 \text{niipgdp}_{^U}^{E} + \beta_3 \text{op}_{^E} + \beta_4 \text{HPI}_{^U}^{E} + \eta_t \]

We then test for stationary residuals in the long run relationships. Table C.3 shows that residuals in the long run relationships are stationary. We can therefore estimate the error correction models for the respective models. The estimation output is available in the core text.

### Table C.3: Critical values for Augmented Dickey Fuller cointegration test

<table>
<thead>
<tr>
<th>Tables</th>
<th>Confidence Level</th>
<th>1 %</th>
<th>5 %</th>
<th>10 %</th>
<th>T-Stat Model 1</th>
<th>T-Stat Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engle and Yoo (1987)</td>
<td>T = 330, N = 4</td>
<td>-4.70</td>
<td>-4.18</td>
<td>-3.89</td>
<td>-5.36</td>
<td>-4.35</td>
</tr>
<tr>
<td>Phillips and Ouliaris (1990)</td>
<td>without constant, without trend</td>
<td>-4.67</td>
<td>-4.13</td>
<td>-3.81</td>
<td>-5.38</td>
<td>-4.35</td>
</tr>
<tr>
<td></td>
<td>with constant, without trend</td>
<td>-5.07</td>
<td>-4.45</td>
<td>-4.16</td>
<td>-5.38</td>
<td>-4.35</td>
</tr>
<tr>
<td></td>
<td>with constant, with trend</td>
<td>-5.36</td>
<td>-4.74</td>
<td>-4.46</td>
<td>-5.36</td>
<td>-4.34</td>
</tr>
<tr>
<td>McKinnon (1991)</td>
<td>with constant, without trend</td>
<td>-5.02</td>
<td>-4.46</td>
<td>-4.16</td>
<td>-5.38</td>
<td>-4.35</td>
</tr>
<tr>
<td></td>
<td>with constant, with trend</td>
<td>-5.33</td>
<td>-4.76</td>
<td>-4.47</td>
<td>-5.36</td>
<td>-4.34</td>
</tr>
</tbody>
</table>

**D. Principles of the Kalman Filter**

State-space models deal with dynamic time series models that involve unobserved variables (Kim and Nelson (1998)). The basic tool to estimate standard state-space model is the Kalman filter. The Kalman filter is a recursive procedure for computing the estimator of the unobserved component or the state vector at time \( t \), based on all available information at time \( t \). State-space models are composed by two equations: a measurement equation and a state equation (or transition equation).

**D.1 Measurement equation**

The measurement equation describes the relation between observed variables (exogenous fundamentals) and unobserved state variables:

\[ y_t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{18} x_{18} + \beta_{19} x_{19} + \beta_{20} x_{20} + \epsilon_t \]
Hence, under a vector form:

\[
y_t = \begin{bmatrix} 1 & x_{1t} & x_{2t} & \ldots & x_{19t} & x_{20t} \end{bmatrix} + \varepsilon_t
\]

\[\rightarrow y_t = x_t \beta_t + \varepsilon_t\]

With \( y_t \), the endogenous variable (the exchange rate); \( x_t \), the exogenous variables (the fundamentals); \( \varepsilon_t \rightarrow iidN(0, Q_t) \); \( y_t = \text{dceurodollar} \); \( x_{it} = \text{indprod}_{EU}^t \);

\[
x_{2t} = \text{indprod}_{US}^t \quad x_{3t} = np_{EU}^t \quad x_{4t} = np_{US}^t \quad x_{5t} = npp_{EU}^t \quad x_{6t} = npp_{US}^t \quad x_{7t} = \text{employ}_{EU}^t \quad x_{8t} = \text{employ}_{US}^t \quad x_{9t} = op_{EU}^t \quad x_{10t} = hpi_{EU}^t \quad x_{11t} = sp_{EU}^t \quad x_{12t} = sp_{US}^t \quad x_{13t} = \text{exp profit}_{EU}^t \quad x_{14t} = \text{exp profit}_{US}^t \quad x_{15t} = \text{divyield}_{EU}^t \quad x_{16t} = \text{divyield}_{US}^t \quad x_{17t} = \text{st int rate}_{EU}^t \quad x_{18t} = \text{st int rate}_{US}^t \quad x_{19t} = \text{lg int rate}_{EU}^t \quad x_{20t} = \text{lg int rate}_{US}^t .
\]

**D.2 State equations**

The state equations (or transition equations) define the dynamics of the state variables. We assume state variables follow a random walk:

\[\beta_t = \beta_{t-1} + \nu_t\]

With \( \nu_t \rightarrow iidN(0, Q_t) \), \( i = 0 \) to \( 20 \)
Hence, under a matrix form:

\[
\begin{bmatrix}
\beta_{0t} \\
\beta_{1t} \\
\beta_{2t} \\
\vdots \\
\beta_{19t} \\
\beta_{20t} \\
\beta_{21t}
\end{bmatrix}
= 
\begin{bmatrix}
1 & 0 & 0 & \ldots & 0 & 0 & 0 \\
0 & 1 & 0 & \ldots & 0 & 0 & 0 \\
0 & 0 & 1 & \ldots & 0 & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & \ldots & 1 & 0 & 0 \\
0 & 0 & 0 & \ldots & 0 & 1 & 0 \\
0 & 0 & 0 & \ldots & 0 & 0 & 1 \\
\end{bmatrix}
\begin{bmatrix}
\beta_{0t-1} \\
\beta_{1t-1} \\
\beta_{2t-1} \\
\vdots \\
\beta_{19t-1} \\
\beta_{20t-1} \\
\beta_{21t-1}
\end{bmatrix}
+ 
\begin{bmatrix}
\nu_{0t} \\
\nu_{1t} \\
\nu_{2t} \\
\vdots \\
\nu_{19t} \\
\nu_{20t} \\
\nu_{21t}
\end{bmatrix}
\]

D.3 Description of the Kalman filter

The Kalman filter is a recursive procedure for computing the optimal estimate of the unobserved-state vector \( \beta_t, t = 1,2,\ldots,T \), based on the appropriate information set, assuming that \( F_t, R_t \) and \( Q_t \) are known. The Kalman filter provides a minimum mean squared error estimate of \( \beta_t \) given the appropriate information set. Depending upon the information set used, we have the basic filter and the smoothing filter. The basic filter refers to an estimate of \( \beta_t \) based on information available up to time \( t \). The smoothing filter is an estimate of \( \beta_t \) based on all the available information in the sample through time \( T \).

The basic Kalman filter is described by two steps: the prediction step and the updating step.

D.3.1 The prediction equations

The prediction equations form at the beginning of time \( t \), an optimal predictor of \( y_t \) based on all the available information up to time \( t-1 \) (\( y_{t-1} \)). To do this, we need to calculate \( \beta_{t-1} \). The prediction equations are defined below:

1/ The estimate of \( \beta_t \) conditional on information up to time \( t-1 \)

\[
\beta_{t/t-1} = F_t \beta_{t-1/t-1}
\]
2/ The covariance matrix of \( \beta_t \) conditional on information up to time \( t-1 \)

\[
P_{t/t-1} = F_t P_{t-1/t-1} F_t' + Q_t
\]

Where \( Q_t \) is the covariance of shocks to \( \beta_t \)

3/ The prediction error

\[
\eta_{t/t-1} = y_t - y_{t/t-1} = y_t - x_t \beta_{t/t-1}
\]

4/ The conditional variance of the prediction error

\[
f_{t/t-1} = x_t P_{t/t-1} x_t + R_t
\]

Where \( R_t \) is the variance of \( \varepsilon_t \)

D.3.2 The updating equations

Once \( y_t \) is realized at the end of time \( t \), the prediction error \( \eta_{t/t-1} \) can be calculated. This prediction error contains new information about \( \beta_t \) beyond that contained in \( \beta_{t/t-1} \). Thus after observing \( y_t \), a more accurate inference can be made of \( \beta_t : \beta_{t/t} \). An inference of \( \beta_t \) based on information up to time \( t \), may be of the following form: \( \beta_{t/t} = \beta_{t/t-1} + K_t \eta_{t/t-1} \)

where \( K_t \) is the weight assigned to new information about \( \beta_t \), contained in the prediction error. The updating equations are defined below:

5/ The estimate of \( \beta_t \) conditional on information up to time \( t \)

\[
\beta_{t/t} = \beta_{t/t-1} + K_t \eta_{t/t-1}
\]
The covariance matrix of $\beta_t$ conditional on information up to time $t$

$$P_{t/t} = P_{t/t-1} - K_t x_t P_{t/t-1}$$

Where $K_t$ is the Kalman gain: $K_t = P_{t/t-1} x_t (f_t^{-1})$.

The Kalman filter is a recursive procedure for computing the optimal estimate of the unobserved state vector $\beta_t$, $t = 1, 2,..., T$, based on the appropriate information set, assuming that $R_t$ and $Q_t$ are known. The parameters to be estimated are the following ones:

$$\theta = (\beta_{01}, \beta_{11}, \beta_{21}, \beta_{31}, \beta_{41}, \beta_{51}, \beta_{61}, \beta_{71}, \beta_{81}, \beta_{91}, \beta_{101},$$
$$\beta_{111}, \beta_{121}, \beta_{131}, \beta_{141}, \beta_{151}, \beta_{161}, \beta_{171}, \beta_{181}, \beta_{191}, \beta_{201}, \beta_{211}, \sigma^2_v,$$
$$\sigma^2_{v01}, \sigma^2_{v11}, \sigma^2_{v21}, \sigma^2_{v31}, \sigma^2_{v41}, \sigma^2_{v51}, \sigma^2_{v61}, \sigma^2_{v71}, \sigma^2_{v81}, \sigma^2_{v91}, \sigma^2_{v101},$$
$$\sigma^2_{v111}, \sigma^2_{v121}, \sigma^2_{v131}, \sigma^2_{v141}, \sigma^2_{v151}, \sigma^2_{v161}, \sigma^2_{v171}, \sigma^2_{v181}, \sigma^2_{v191}, \sigma^2_{v201}, \sigma^2_{v211})$$

The parameters can be estimated by maximising the following log likelihood function with respect to the parameters of the model:

$$\ln L = -\frac{1}{2} \sum_{t=1}^{T} \ln(2\pi f'_{t/t-1}) - \frac{1}{2} \sum_{t=1}^{T} \eta_{t/t-1} f_{t/t-1}^{-1} \eta_{t/t-1}$$

Where $f_{t/t-1}$ and $\eta_{t/t-1}$ are provided by the Kalman filter.
General Conclusion:
What Lessons can we Draw from this Thesis?

For more than four decades now, economists stick to the REH-EMH hypotheses for lack of better alternative hypotheses but also because assuming economic agents are rational is convenient from a modelling perspective. The REH-EMH paradigm is the basis of traditional models of exchange rate determination. However, Meese and Rogoff (1983) and later Cheung, Chinn and Garcia Pascual (2005) show that exchange rate models based on the REH-EMH theory provide low explanatory and predictive powers concerning exchange rate dynamics. Besides, the REH-EMH paradigm is unable to resolve exchange rate puzzles such as the disconnection puzzle, the excess volatility puzzle and the forward premium puzzle. Many researchers ask about the relevance of the REH-EMH hypotheses and have reconsidered such hypotheses.

In this thesis we have attempted to provide an alternative way of thinking about exchange rate dynamics. The aim of this thesis is to provide advances in the modelling of exchange rate dynamics. The objective is to set models that provide better explanatory and predictive powers of currency movements than traditional exchange rate models. To achieve this task, we depart from the hypotheses assumed by traditional models - the REH-EMH paradigm and the linear structures. Instead, we draw inspirations from behavioural finance and non-linear econometrics. The main result of this thesis is that market agents’ behaviours and macroeconomic fundamentals are both important determinants of exchange rate dynamics. We emphasise in this thesis that beyond macroeconomic fundamentals, researchers should consider market agents’ behaviours in order to understand exchange rate dynamics.

The first article analyses the efficiency of the foreign exchange market and sets the limits of the REH-EMH paradigm.

Starting from the internal contradictions of Fama (1965)’s definition of efficiency, we split market efficiency into multiple and independent forms: fundamental efficiency, speculative efficiency, macroeconomic efficiency and pure inefficiency. We associate a set of empirical tests to each form of efficiency. Results show that in the short run (between 1 month and 1 year) pure inefficiency prevails in the foreign exchange market. In the medium run (between 1 year and 2 years), speculative efficiency characterises foreign exchange market
efficiency. In the long run (from 5 years on), macroeconomic efficiency holds in the foreign exchange market. Fundamental efficiency - Fama’s efficiency - is rejected in the foreign exchange market at all horizons. The rejection of fundamental efficiency is due to the fact that the REH-EMH paradigm does not hold empirically in the foreign exchange market.

This article argues that exchange rate dynamics are determined not solely by fundamentals forces (macroeconomic variables) but also by non-fundamental forces (agents’ behaviours). Non-fundamental forces tend to dominate fundamental forces in the determination of exchange rates at short/medium run horizons, while in the long run fundamental forces contribute more to explain currency movements than non-fundamental forces.

There are several possible extensions to this work. First, tests of foreign market efficiency can be extended to other types of exchange rates (for instance, effective exchange rates) or other bilateral exchange rates (for example, exchange rates from emerging economies). Secondly, one could provide better empirical tests for each form of efficiency by relying on new datasets or new econometric techniques. For instance, testing UIP and REH at higher frequencies by relying on tick-by-tick data could be the start of an interesting way of research.

The second article provides elements to understand the impressive success of order flows models in the determination of exchange rates. We investigate inside the black box of order flows models to understand why order flows provide better explanatory and predictive powers of exchange rate dynamics relative to traditional models.

We set a theoretical model that regroups a behavioural exchange rate model and a microstructure model. Our objective is to observe how new information is embedded into the final price of currencies. The article offers three results. First, simulations of the theoretical model replicate important stylized facts observed empirically in the foreign exchange market. In the short run, the exchange rate is disconnected from its fundamentals but not from order flows. In the long run, the exchange rate returns towards its fundamental value and remains still close to order flows. Secondly, the article argues that the foreign exchange market is intrinsically inefficient. Indeed, information is distorted at two levels in the market. On the one hand, information is distorted by behavioural noise triggered by agents' behaviours. On the other hand, information is distorted by microstructure noise generated by the trading mechanism peculiar to the foreign exchange market. Thirdly, the article claims that the outstanding performances of order flows models relative to traditional models of exchange
rate are attributed to the fact that order flows models do not share the same information set. Order flows contain information that has been processed by market agents while traditional models only consider unprocessed information about exchange rate fundamentals. More precisely, processed information covers the time-varying weight of fundamental information (both public and private), behavioural information (both public and private) and microstructure information. Unprocessed information includes only public fundamental information.

This article argues that the main advantage of order flows models is to take account of market agents’ behaviours. This argument explains why order flows offer more satisfying results in the determination of exchange rate dynamics at (very) short run horizons than traditional exchange rate models.

The first extension of this work is to define empirical tests to check whether the conclusions from the theoretical model hold empirically. The second extension could aim at countering the black box problem of order flows. Researchers could develop a full model of order flows determination and test it empirically.

The third article identifies the determinants of heterogeneous behaviours in the foreign exchange market and in stock markets.

We show that behaviours’ heterogeneity significantly explains asset price dynamics in the foreign exchange market and in stock markets. Moreover, heterogeneous behaviours are homogenous across markets. This homogeneity becomes more acute through the process of financial integration between the foreign exchange market and stock markets. We then analyse which variables are likely to determine heterogeneous behaviours. We find that risk aversion (as proxied by implied volatility on option prices) is more likely to explain agents’ behaviours in financial markets than macroeconomic fundamentals. When risk aversion is high, fundamentalists dominate the market. Conversely, when risk aversion is low, the market is globally chartist. In other words, fundamentalists dominate in times of crisis (when risk aversion increases) while chartists dominate in times of economic boom (when risk aversion decreases). From a behavioural perspective, agents seem therefore more rational in times of crisis (since they rely more on fundamentals to forecast asset prices) than in times of booms (where agents rely more on chartist analysis and ignore fundamentals).

Based on this stylised fact we build a behavioural forecasting rule. This rule provides better out-of-sample forecasts of future asset prices than the random walk. This observation stands in the long run as well as in the short run.
This article thus proves that taking account of stylised facts in agents’ behaviours is useful for explaining and forecasting asset price dynamics.

Further research is needed to find other determinants of heterogeneous behaviours in financial markets. One could also refine the testing procedure used to identify the determinants of heterogeneous behaviours. For sake of precisions, one could test in STAR models a time-varying value for the threshold parameter (instead of a constant one, as considered in our analysis).

The fourth article sets an unorthodox model of exchange rate determination based on conventions that prevail among agents in the foreign exchange market.

The paper proposes a theoretical model to show how conventions are built by agents in the market. The structure of the theoretical model borrows elements from the Imperfect Knowledge Economics approach (Frydman and Goldberg (2007)). The simulated exchange rate from the theoretical convention model replicates several stylised facts highlighted empirically in exchange rate dynamics. We test empirically the theoretical model on the euro/dollar exchange rate between January 1995 and December 2008. In a first step, we rely on a macroeconomic analysis to highlight the conventions that prevail on the euro/dollar exchange rate. In a second step, we build an econometric approach to find market conventions. We use a time-varying parameters model to find the most important fundamentals in the determination of the euro/dollar exchange rate. The macroeconomic analysis and the econometric approach end up with the same results. Both analyses show that the market tends to switch between periods of optimism and periods of pessimism. Moreover, switches between fundamentals considered in a bull convention and in a bear convention explain the dynamics of the euro/dollar exchange rate. Finally, forecasting tests show that the convention model offers better exchange rate forecasts at horizons longer than 1 month relative to traditional models of exchange rate and to the simple random walk.

Several improvements can be brought to the convention model. First, one can endogenise the choice of fundamentals in the convention model by relying directly on a financial media. Indeed, as financial media play a major role in the building and the collapse of market conventions, one could think about an algorithm that select the most cited news in financial media (such as Reuters or Bloomberg) and then put this news as an explanatory variable into the convention model. Secondly, instead of relying on fundamentals released at low frequencies by Datastream (monthly or annually), one could consider scheduled news about exchange rate fundamentals that hit the market periodically at higher frequencies. Such
scheduled news are available in Bloomberg at daily frequencies. Thirdly, as the convention model offers promising results to explain and predict exchange rate dynamics, it could be interesting to extend the convention model to other assets (stocks and commodities) in order to assess the robustness of convention theory.

Still, at shorter horizons a lot of research remains to be done to improve asset pricing models based on agents’ behaviours. This thesis provides only modest advances in this field of research. At longer horizons researchers could implement asset pricing models based on behavioural finance into more complex models such as economy wide models. These more complex structures may help taking account of all the endogenous factors that affect asset price dynamics.
Conclusion Générale :
Quels Enseignements Peut-on Tirer de cette Thèse ?


Dans cette thèse, nous avons introduit une manière alternative de penser la dynamique des taux de change. L’objectif est de construire des modèles de change qui fournissent des pouvoirs explicatifs et prédictifs meilleurs que ceux des modèles traditionnels de change. Pour répondre à cet objectif, nous délaissons les hypothèses de base des modèles traditionnels de change - l’HAR-HEM - et l’hypothèse de linéarité entre dynamique du change et fondamentaux macroéconomiques. Nous tirons plutôt des leçons des enseignements apportés par la finance comportementale et l’économétrie non-linéaire.

Le résultat principal de cette thèse est que les fondamentaux macroéconomiques ainsi que les comportements des agents sont des déterminants essentiels pour comprendre la dynamique des taux de change.

Le premier article analyse l’efficience du marché des changes et établit les limites du paradigme de l’HAR-HEM. Partant des contradictions internes de la définition de l’efficience selon Fama (1965), nous décomposons l’efficience des marchés en des formes multiples et indépendantes: l’efficience fondamentale, l’efficience spéculative, l’efficience macroéconomique et l’inefficience pure. Nous définissons des tests empiriques pour chaque forme d’efficience. Les résultats montrent que le marché des changes est caractérisé par l’inefficience pure à court terme (entre 1 mois et 1 an); l’efficience spéculative à moyen terme (entre 1 an et 2 ans) et l’efficience macroéconomique à long terme (à partir de 5 ans). L’efficience fondamentale est rejetée pour tous les horizons sur le marché des changes. Ce
dernier résultat est justifié notamment par le rejet de l’hypothèse d’anticipations rationnelles quelque soit l’horizon considéré.

Cet article suggère que la dynamique des taux de change est déterminée non seulement par des forces fondamentales (les fondamentaux macroéconomiques) mais également par des forces non-fondamentales (les comportements des agents sur les marchés financiers). Les forces fondamentales dominent celles fondamentales dans la détermination du taux de change à court/moyen terme ; alors qu’à long terme les forces fondamentales contribuent plus à expliquer les mouvements du change que les forces non-fondamentales.

Plusieurs extensions de l’article sont possibles. En premier lieu, les tests de l’efficience du marché des changes peuvent être appliqués à d’autres types de taux de change (les taux de change effectifs par exemple) ou à d’autres taux de change bilatéraux (notamment les taux de change des économies émergentes). En second lieu, des tests plus robustes peuvent être définis pour chaque forme d’efficience. Nous pouvons ainsi se baser sur de nouveaux échantillons de données et/ou de nouvelles techniques économétriques. Par exemple, la PTINC ainsi que l’HAR pourraient être testées sur des horizons de très court terme, en tenant compte de données tick-by-tick.

Le deuxième article fournit des éléments pour comprendre le succès des modèles à flux d’ordre dans la détermination des taux de change. Nous enquêtons à l’intérieur de la boîte noire des modèles à flux d’ordre afin de comprendre pourquoi les flux d’ordre fournissent des pouvoirs explicatifs et prédictifs plus élevés que les modèles traditionnels de taux de change.

Nous construisons un modèle théorique se composant d’un modèle à agents hétérogènes et d’un modèle de microstructure. L’objectif est d’observer comment l’information nouvelle est introduite dans le prix final des devises. Cet article présente trois résultats principaux. Premièrement, les simulations du modèle théorique répliquent d’importants faits stylisés observés empiriquement sur le marché des changes. Ainsi à court terme, le taux de change apparaît déconnecté des fondamentaux alors qu’à long terme, il retourne vers sa valeur fondamentale. Les flux d’ordre sont quant à eux fortement corrélés à la dynamique du change, à court terme comme à long terme. Deuxièmement, l’article suggère que le marché des changes est intrinsèquement inefficent. En effet, l’information est déformée à deux niveaux dans le marché. L’information est déformée d’une part par le bruit lié au comportement des agents et d’autre part par le bruit de microstructure généré par le mécanisme d’échange propre au marché des changes. Troisièmement, l’article justifie les meilleures performances empiriques des modèles à flux d’ordre relativement aux modèles
traditionnels de change par la considération d’un stock d’information différent entre les deux modèles. En effet, les flux d’ordre contiennent de l’information qui a déjà été traitée par les agents sur le marché. Cette information traitée recouvre l’information fondamentale (publique et privée), l’information liée aux comportements des agents et l’information propre à la microstructure du marché. A contrario, les modèles traditionnels considèrent uniquement une information brute, non traitée par les agents ; soit l’information publique sur les fondamentaux. Cet article suggère que l’avantage principal des modèles à flux d’ordre est de tenir compte de la composante psychologique du change (i.e. le comportement des agents). Cet argument explique le succès des modèles à flux d’ordre dans la prévision du change à (très) court terme relativement aux modèles traditionnels de change.

Une première extension de cet article consisterait à tester empiriquement les conclusions issues du modèle théorique. Une seconde extension serait de développer un modèle plus complet décomposant toute l’information contenue dans le flux d’ordre et de tester ce modèle empiriquement.

Le troisième article identifie les déterminants des comportements hétérogènes dans le marché des changes et sur les marchés boursiers. Nous montrons que les modèles à agents hétérogènes expliquent significativement la dynamique des prix des devises et celle des actifs boursiers. De plus, les comportements hétérogènes sont homogènes entre marchés financiers. Cette homogénéité reflète le processus d’intégration financière entre le marché des changes et les marchés boursiers. Nous analysons également les déterminants des comportements hétérogènes. Les résultats montrent que l’aversion au risque (approchée par la volatilité implicite sur les prix d’option) explique la dynamique des comportements hétérogènes contrairement aux fondamentaux macroéconomiques. Ainsi, lorsque l’aversion au risque est élevée, les fondamentalistes dominent le marché tandis que lorsque l’aversion au risque est faible, les chartistes dominent le marché. En d’autres termes, les fondamentalistes dominent en temps de crise (quand l’aversion au risque augmente) alors que les chartistes dominent en temps d’expansion économique (lorsque l’aversion au risque est faible). D’un point de vue comportemental, cela signifie que les agents sont plus rationnels en temps de crise (puisqu’ils tiennent compte des fondamentaux pour former leurs anticipations) qu’en temps d’expansion économique (où les agents s’appuient sur des techniques chartistes et ignorent l’information sur les fondamentaux). Sur la base de ce fait stylisé, nous construisons une règle de prévision basée sur les comportements des agents. Cette règle fournit de meilleures prévisions en dehors
de l’échantillon que le modèle de marche aléatoire. Ce fait est observé à long terme comme à court terme.

Cet article montre ainsi que la prise en compte de faits stylisés sur les comportements des agents est utile pour expliquer et prévoir la dynamique des prix d’actifs. Des travaux complémentaires sont nécessaires afin de trouver d’autres déterminants des comportements hétérogènes. Egalement, les tests économétriques pourraient être affinés en considérant par exemple une valeur seuil variable dans le temps dans le modèle STAR (dans notre article, cette valeur seuil est constante dans le temps).

Le quatrième article construit un nouveau modèle de détermination des taux de change basé sur les conventions prévalant entre agents dans le marché des changes. L’article propose un modèle théorique qui décrit la formation des conventions dans le marché des changes. Le taux de change simulé à partir du modèle théorique réplique d’importants faits stylisés observés sur la dynamique du change au niveau empirique. Nous testons empiriquement le modèle à convention sur le taux de change euro/dollar entre janvier 1995 et décembre 2008. Nous considérons deux approches.

Dans un premier temps, nous utilisons une analyse macroéconomique pour mettre en évidence les conventions présentes sur le taux de change euro/dollar. Dans un second temps, nous construisons une approche économétrique afin de mettre en évidence les conventions présentes dans le marché. Nous estimons pour cela un modèle à coefficients variables dans le temps. L’analyse macroéconomique et l’approche économétrique débouchent sur les mêmes conclusions. Le marché tend à alterner entre des périodes d’optimisme et des périodes de pessimisme. Plus précisément, la dynamique du taux de change euro/dollar est expliquée par l’alternance entre les fondamentaux considérés dans la convention optimiste et dans celle pessimiste. Enfin, les tests de prévisions montrent que pour des horizons supérieurs à 1 mois le modèle à convention fournit de meilleures prévisions en dehors de l’échantillon que les modèles traditionnels de change et que la marche aléatoire.

Nombreuses sont les améliorations qui peuvent être apportées au modèle à convention. Une première extension vise à endogénéiser le choix des fondamentaux dans le modèle à convention en s’appuyant directement sur les sociétés d’information financière. En effet, ces sociétés d’information financières jouent un rôle majeur dans la formation et la disparition des conventions. Nous pourrions ainsi construire un algorithme qui sélectionne les nouvelles macroéconomiques les plus citées de la part des médias financiers (tels que Reuters ou Bloomberg) puis qui les inclut dans le modèle à convention en tant que variables explicatives.
Deuxièmement, au lieu d’utiliser des fondamentaux publiés à des fréquences mensuelles voire annuelles par Datastream, nous pourrions considérer les nouvelles périodiques sur les fondamentaux macroéconomiques du taux de change publiées à des fréquences plus élevées. De telles données sont disponibles sur Bloomberg à des fréquences journalières. Troisièmement, étant donné que le modèle à convention offre des résultats satisfaisants concernant l’explication et la prédiction des taux de change, ce modèle pourrait être appliqué à d’autres actifs financiers (tels que les actions et les matières premières). Ces travaux permettraient de tester la robustesse du modèle à convention.

En somme, de nombreux travaux sont encore nécessaires à court terme pour améliorer la spécification des modèles de détermination des prix d’actifs basés sur les comportements des agents sur les marchés financiers. Cette thèse fournit quelques avancées, sommes toutes modestes. À plus long terme, les chercheurs pourraient intégrer les modèles comportementaux de détermination des prix d’actifs dans des modèles plus complexes représentant une économie dans son intégralité. Ces modèles plus complexes tiendront compte de tous les facteurs endogènes affectant la dynamique des prix d’actifs.
Abstract

The starting point of the thesis is the failure of traditional exchange rate models to explain and forecast exchange rate dynamics. The challenge of the thesis is therefore to look for models that provide better explanatory and predictive powers of exchange rate dynamics than traditional exchange rate models. In an attempt to build such models, we draw lessons from behavioural finance and nonlinear econometrics.

The first article justifies the failure of traditional models by showing that the hypotheses underlying these models (EMH and REH) are not verified empirically in the foreign exchange market. It also shows the limit of considering only macroeconomic fundamentals as a determinant of exchange rate dynamics. The second article analyses the success of order flows models and shows the necessity of considering agents’ behaviours (market psychology) to find a robust and successful model of exchange rate determination. The third article explains exchange rate dynamics by modelling heterogeneous behaviours. It shows that a forecasting rule based on stylised facts about agents’ behaviours in the market provides better forecasts of future exchange rates than the simple random walk at short and long run horizons. The fourth article proposes an unorthodox model of exchange rate dynamics based on conventions that prevail in the foreign exchange market. Results show that based on the same information set, the convention model significantly improves the performances of traditional models when it comes to forecasting exchange rates.

The main message of the thesis is that macroeconomic fundamental as well as agents’ behaviours are both essential components to explain and forecast exchange rate dynamics.

Keywords: Exchange Rate, Behavioural Finance, Nonlinear Econometrics
Essais sur la Modélisation de la Dynamique du Taux de Change
à travers les Enseignements de la Finance Comportementale

Résumé

Le point de départ de la thèse est l’échec des modèles traditionnels de détermination des taux de change dans l’explication et la prédiction de la dynamique des taux de change. L’objectif de la thèse est de trouver un modèle qui fournit de meilleurs pouvoirs explicatifs et prédictifs des taux de change relativement aux modèles traditionnels de change. Pour cela, nous tirons des enseignements de la finance comportementale et de l’économétrie non-linéaire.

Le premier article justifie l’échec des modèles traditionnels de change en montrant que les hypothèses sous-jacentes à ces modèles (HAR et HEM) ne sont pas vérifiées empiriquement. L’article montre également que la considération unique des fondamentaux macroéconomiques est insuffisante pour expliquer correctement la dynamique des taux de change. Le deuxième article analyse le succès des modèles à flux d’ordre. Cet article montre la nécessité de considérer le comportement des agents (la psychologie du marché) pour construire un modèle de détermination des taux de change robuste et satisfaisant. Le troisième article explique la dynamique des taux de change en modélisant les comportements hétérogènes des agents. Cet article montre qu’une règle de prédiction basée sur un fait stylisé concernant les comportements des agents sur le marché fournit de meilleures prévisions des taux de change futurs que le modèle de marche aléatoire pour des horizons de court terme et de long terme. Le quatrième article propose un modèle non conventionnel de détermination des taux de change basé sur les conventions prévalant entre agents dans le marché des changes. Cet article montre qu’en considérant le même stock d’information, le modèle à convention fournit de meilleures performances prédicitives des taux de change que les modèles traditionnels.

Le message principal de la thèse est que les fondamentaux macroéconomiques et les comportements des agents sont tous deux des déterminants essentiels pour expliquer et prévoir la dynamique des taux de change.

Mots-clés: Taux de Change, Finance Comportementale, Econométrie Non-Linéaire
Vu: le Président
M.

Vu: les suffragants
MM.

Vu et permis d'imprimer:
Le Vice-Président du Conseil Scientifique chargé de la Recherche de l'Université PARIS DAUPHINE.
Essays in Exchange Rate Dynamics Modelling  
Through Lessons from Behavioural Finance

Abstract

The starting point of the thesis is the failure of traditional exchange rate models to explain and forecast exchange rate dynamics. The challenge of the thesis is therefore to look for models that provide better explanatory and predictive powers of exchange rate dynamics than traditional exchange rate models. In an attempt to build such models, we draw lessons from behavioural finance and nonlinear econometrics. The first article justifies the failure of traditional models by showing that the hypotheses underlying these models (EMH and REH) are not verified empirically in the foreign exchange market. It also shows the limit of considering only macroeconomic fundamentals as a determinant of exchange rate dynamics. The second article analyses the success of order flows models and shows the necessity of considering agents’ behaviours (market psychology) to find a robust and successful model of exchange rate determination. The third article explains exchange rate dynamics by modelling heterogeneous behaviours. It shows that a forecasting rule based on stylised facts about agents’ behaviours in the market provides better forecasts of future exchange rates than the simple random walk at short and long run horizons. The fourth article proposes an unorthodox model of exchange rate dynamics based on conventions that prevail in the foreign exchange market. Results show that based on the same information set, the convention model significantly improves the performances of traditional models when it comes to forecasting exchange rates. The main message of the thesis is that macroeconomic fundamental as well as agents’ behaviours are both essential components to explain and forecast exchange rate dynamics.

Keywords: Exchange Rate, Behavioural Finance, Nonlinear Econometrics

Essais sur la Modélisation de la Dynamique du Taux de Change  
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Résumé

Le point de départ de la thèse est l’échec des modèles traditionnels de détermination des taux de change dans l’explication et la prédiction de la dynamique des taux de change. L’objectif de la thèse est de trouver un modèle qui fournit de meilleurs pouvoirs explicatifs et prédicatifs des taux de change relativement aux modèles traditionnels de change. Pour cela, nous tirons des enseignements de la finance comportementale et de l’économétrie non-linéaire. Le premier article justifie l’échec des modèles traditionnels de change en montrant que les hypothèses sous-jacentes à ces modèles (HAR et HEM) ne sont pas vérifiées empiriquement. L’article montre également que la considération unique des fondamentaux macroéconomiques est insuffisante pour expliquer correctement la dynamique des taux de change. Le deuxième article analyse le succès des modèles à flux d’ordre. Cet article montre la nécessité de considérer le comportement des agents (la psychologie du marché) pour construire un modèle de détermination des taux de change robuste et satisfaisant. Le troisième article explique la dynamique des taux de change en modélisant les comportements hétérogènes des agents. Cet article montre qu’une règle de prévision basée sur un fait stylisé concernant les comportements des agents sur le marché fournit de meilleures prévisions des taux de change futurs que le modèle de marché aléatoire pour des horizons de court terme et de long terme. Le quatrième article propose un modèle non conventionnel de détermination des taux de change basé sur les conventions prévalant entre agents dans le marché des changes. Cet article montre qu’en considérant le même stock d’information, le modèle à convention fournit de meilleures performances prédictives des taux de change que les modèles traditionnels. Le message principal de la thèse est que les fondamentaux macroéconomiques et les comportements des agents sont tous deux des déterminants essentiels pour expliquer et prévoir la dynamique des taux de change.

Mots-clés: Taux de Change, Finance Comportementale, Econométrie Non-Linéaire