Measurement, Dynamics, and Implications of Heterogeneous Beliefs in Financial Markets

Measurement, Dynamics, and Implications of Heterogeneous Beliefs in Financial Markets

De meting, dynamiek, en implicaties van heterogene opvattingen in financiële markten

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In the spirit of Socrates, obtaining a PhD degree has brought me to the often frustrating limits of what I know (never enough) and what I want to know (everything). What is a bit disturbing – but at the same time soothing as well - is that I started to realize that even the smartest and most influential people have these limits. And, they don't always seem to realize they do. This 'overconfidence' bias may be one of the most common, and perhaps one of the most detrimental, biases to suffer from when you are a manager or investor. Realizing that people suffer from such psychological biases and that it can affect their professional performance is interesting in itself. Realizing that, when investors suffer from such biases, it may have very serious effects for financial markets was interesting enough to start this PhD.

The subjects of behavioral finance and heterogeneous agent models may have never caught my attention if it wasn't for my current co-supervisor, Remco Zwinkels. Actually, a lot of things may have never caught my attention if it wasn't for him. Remco, thanks for sparking my enthusiasm for this subject, pursuing a PhD, going to Sydney for a research visit (although I was easily convinced), presenting at numerous conferences, and teaching a full course. All these made my time as a PhD Candidate much richer. I would also like to thank you for the freedom you gave me to work on topics that I found interesting, so that I could learn along the way what it is like to be an academic researcher. And above all, thanks for all the great conversations (and gossip conversations) we had when we did not talk about research. You are both a fantastic researcher and a great person, and I honestly couldn't have wished for a better ("daily") supervisor.

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Whereas the marathon was one of my 'sportive' highs during the PhD, one of my professional highs was organizing the first Research in Behavioural Finance Conference, together with Martijn and Remco, and with the invaluable support of Daan. This was a very time-consuming process, but the ability to work in such a great team and the grand success of the conference made every hour worth it.

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I thoroughly enjoyed the past years - without all these people, my time as a PhD Candidate wouldn't have been nearly as fun.

Saskia ter Ellen

Oslo, March 2015

Contents

1 Introduction and outline

1.1 Heterogeneity

"*We inhabit a universe that is characterized by diversity*." – Desmond Tutu

Our world is characterized by diversity in infinite dimensions. There are countless examples already in the human spectrum alone. There is diversity among people in obvious ways, such as age, gender, ethnicity and culture. Then there are the differences that are less easily observable, such as physical and mental strength, skills and abilities, religion, generosity. And there is a diversity of experiences, beliefs, and preferences, that may or may not be related to the differences mentioned before. Yet, in the majority of textbooks and research papers in economics and finance, agents, (economic) actors, investors, and the like are assumed to have the same beliefs and preferences and act in the same ways. Have these economists forgotten that the main drivers of their primary study object, the economy, are in fact people? You may call them actors, agents, investors, or any other name, but at the core it comes down to the same: people, human beings, who may or may not be rational, who may or may not behave in a homogeneous way, who may or may not behave the same individually as they do in groups. Of course, there is no way we can incorporate all the diversity there is in a well-functioning, comprehensive model of the economy. But we can work towards a stylized model that is more representative of the world around us. And in my opinion, relaxing the assumption of homogeneous beliefs and preferences is crucial.

This dissertation is part of a growing research field in which the diversity of human beings, as economic actors, is slowly incorporated. Instead of diversity, a more accepted term in economics and finance is heterogeneity. In the rest of the introduction I will first set out how research in finance is slowly moving from classical homogenous and rational agents models to an increasing amount of behavioral and heterogeneous agent models. Finally, I will summarize the rest of the chapters and how they relate to the current debate on investor heterogeneity and the different components of the title of this dissertation: measurement, dynamics, and implications of heterogeneous beliefs.

1.2 From rational expectations to bounded rationality

The efficient markets hypothesis (EMH), and rational expectations as a crucial assumption for this theory, have been important building blocks for financial theory and economic models for several decades. Although economists have always been aware that not all market participants are fully rational, it was assumed that the main share of them was able to incorporate all available information in an efficient way in order to have an optimal forecast of the future and make optimal decisions. In this framework, it is not a necessary condition that all market participants are rational in order to have efficient markets. According to Friedman, so-called noise traders would be driven out of the market by sophisticated rational agents. Throughout the years, empirical evidence such as observed excessive trading (Milgrom and Stokey, 1982), financial market anomalies, psychological biases (Tversky and Kahneman, 1974; among others) and survey evidence on expectations (Dominguez, 1986; among others), showed that the reality on financial markets could not be fully described by rational expectations models.

This empirical evidence resulted in the emergence of behavioral finance as a new academic field. The behavioral finance literature developed in two dimensions: beliefs and preferences. Kahneman and Tversky (1974, 1979) played a big role in the advancement of both. With respect to preferences, they presented their "Prospect Theory". As opposed to the conventional wisdom at the time, prospect theory predicts that people are loss averse, risk averse over gains, risk seeking over losses (both compared to some agent-specific reference point), and overweight small probabilities. With respect to beliefs, they showed, mostly by running (lab) experiments, that people are subject to severe biases, which makes them unable to act in a rational way when making decisions. Examples of biases that have relevance for finance are representativeness, anchoring, conservatism (Edwards (1968)), overconfidence (Fischhoff et al. (1977)) and status quo bias (Samuelson & Zeckhauser (1988)). Literature on such biases has been growing rapidly over the past decades, to an extent that even overview articles can only cover a part of them (e.g. Hirshleifer, 2001; Barber and Odean, 2013). Shiller (2003) provides an excellent overview of the evolvement of the field of behavioral finance.

Inherent to the rational agent models is the assumption of homogeneity. After all, there is only one way to be rational and thus the actors in the economy can be modeled as one 'representative agent'. There are, however, infinite ways to be irrational. A substantial part of the behavioral finance literature therefore focuses on the heterogeneous nature of economic agents. In this dissertation I will explain and employ some models that acknowledge and incorporate the heterogeneity of financial market participants. More specifically, the focus is on the estimation of dynamic heterogeneous agent models (HAM) that have their roots in the agent-based literature. This branch of behavioral finance assumes that agents are boundedly rational (Simon, 1975), and that they use certain rules of thumb in order to form expectations about future asset prices. This setup was first proposed by Zeeman (1974), and was further advanced by, amongst others, Frankel & Froot (1987b), Chiarella (1992), Brock & Hommes (1997, 1998), Lux (1998) and De Grauwe & Grimaldi (2006). Although different names are being used in the literature for different forecasting strategies, they roughly come down to two or three types of agents. The first type of agent uses past price movements to predict future returns. The strategy this agent uses is referred to as (trend) extrapolation, technical analysis, bandwagon (for positive trend extrapolation), contrarian (for trend reversion) or chartism. The second type of agent bases his expectations on the deviation of the asset price from its fundamental value. This agent is said to be mean reverting, regressive or fundamentalist. Third or fourth types differ among studies and markets. Heterogeneous agent models usually use the distinction between chartists and fundamentalists. A crucial component of heterogeneous agent models is that the weights of different groups of market participants are not stable over time. Instead, market participants can 'switch' between groups. This switching, together with the destabilizing behavior of some of the groups, generates most of the market dynamics that we observe.

1.3 Measurement, dynamics, and implications of heterogeneous beliefs

In this dissertation, I will consider the measurement, dynamics and implications of heterogeneous beliefs in financial markets. For a large part, I will build upon the heterogeneous agent models mentioned before. As such, I will measure the type of heterogeneous beliefs, the dynamics of these different types of beliefs, and the implications of such beliefs in Chapters 3 and 4. In Chapter 5 I will deviate from the heterogeneous agent models and consider a widely used variable to measure the current level of heterogeneity: dispersion in analyst forecasts, also referred to as disagreement. This dissertation is an extension of the heterogeneous agents literature as described above. However, it is also an attempt to close the gap between a specific branch of literature that I label 'agent-based' literature and a wider branch of literature labeled 'behavioral finance' literature.

In Chapter 2[1] I survey the literature on empirical estimation of heterogeneous agents models, i.e. models that incorporate the (dynamics of the) beliefs of different types of investors, and explain how the terminology of this literature relates to the terminology used in other branches of behavioral finance. I will also give a more detailed overview of the evolvement of the behavioral finance literature in this chapter.

In Chapter 3[2], I analyze how investors in the foreign exchange market form expectations and whether they update these expectations based on several factors. To get a better understanding of their expectation formation process, I use a dataset of investor expectations. This is a survey dataset from FX Week which contains forecasts at the weekly frequency from a large number of wholesale investors for several exchange rates and forecast horizons. First of all, I investigate whether investors' expectations are heterogeneous by assessing the fit of various forecasting rules. I distinguish three different general rules that are well-known foreign exchange forecasting strategies: a momentum rule, a PPP rule and an interest parity rule.

[1] Chapter 2 is partly based on my master's thesis: "Ellen, ter S. (2010), Heterogeneous forecasting rules in the foreign exchange market: evidence from survey data, Erasmus University Rotterdam master's thesis."

[2] Chapter 3 is based on "Ellen, ter S. (2010), Heterogeneous forecasting rules in the foreign exchange market: evidence from survey data, Erasmus University Rotterdam master's thesis." and "Ellen, ter S., W.F.C. Verschoor and R.C.J. Zwinkels (2013), Dynamic expectation formation in the foreign exchange market, Journal of International Money and Finance."

These rules have an academic base but are also often used in industry. Furthermore, I assess whether investors change the way they form their expectations over time and for different forecasting horizons. From earlier literature, we can expect that investors update their beliefs when relative performance of the forecasting strategies changes, use more fundamentals-based forecasting rules such as purchasing power parity (PPP) or uncovered interest parity (UIP) for forecasts of longer horizons (say, for a year or more ahead), and use non-fundamentals-based trading rules such as momentum or carry trade for forecasts of short horizons (say, for up to one to three months ahead). The methodology I apply in this method is very much related to that used in the empirical estimation of heterogeneous agents models (HAM), which I elaborate on in Chapter 2.

In Chapter 4[3] I focus on the implications of heterogeneous beliefs during the European sovereign debt crisis. In this chapter I investigate whether heterogeneity of investors and dynamics in their beliefs can explain the escalation of sovereign credit default swap (CDS) spreads and the widening variations across European sovereigns following the Global Financial Crisis (GFC). While controlling for changes in global risk (re)pricing, I examine whether the widespread escalation in European sovereign CDS spreads were the effect of weakened fundamentals in combination with increasing market-wide momentum,. In order to do this, I first develop a pragmatic method to compute fundamentals-based sovereign CDS spreads, as there are no readily available models to compute fundamental values for this asset class[4]. The computation of these fundamental spreads is a combination of extracting risk neutral hazard rates from a reduced form CDS pricing model and regressing those on a number of financial and economic variables that affect the default probability of a country. After having established this I develop and estimate a model for the pricing of CDS spreads based on heterogeneous expectations. The heterogeneous agent paradigm can be merged with more traditional credit pricing theories as follows. The expectation of each investor is a weighted average of fundamental and momentum (chartist) expectations. Fundamental expectations of future sovereign CDS spread movements are based on the state of the

[3] Chapter 4 is based on "Chiarella, C., S. ter Ellen, X. He, E. Wu (2014), Fear or Fundamentals? Heterogeneous Beliefs in the European Sovereign CDS Market, Journal of Empirical Finance."

[4] This in contrast to some other asset classes, such as equity and foreign exchange. In these asset classes there may not be agreement on which is the right model, but one may have reasons to choose one over the other.

country's fundamentals and the ability of the market to price this. Momentum expectations are formed based on the belief of persistence in trends (or trend reversals) in credit risk. On top of these fundamental and momentum expectations, CDS spreads are driven by an extra premium, often referred to as the 'credit risk premium'. The credit risk premium depends on the time-varying willingness of investors to be exposed to the variability in CDS spreads and thus the price they require to bear the volatility risk in sovereign CDS markets. In other words, the credit risk premium captures investors' average risk appetite. I estimate the model with fixed and time-varying weights for both groups. This allows me to evaluate whether dynamic switching between a momentum and fundamental strategy has had an additional impact on European sovereign CDS spreads.

I further study the measurement of heterogeneous beliefs in Chapter 5[5], where I use a similar set of survey expectations as in Chapter 3, this time from Consensus Economics, to assess whether cross-sectional dispersion between those forecasts, labeled as 'disagreement', is a good proxy for heterogeneity or for uncertainty. Despite the fact that the literature on dispersion of beliefs is quite extensive, a solid conclusion about the different interpretation of disagreement has not been reached. Arguments for disagreement being a measure of heterogeneity or uncertainty are appealing for both interpretations. If there is high uncertainty about future exchange rate movements, distance between forecasts is large (i.e. agents heavily disagree about their point forecasts). However, the distance between forecasts may also be large because investors (prefer to) have different forecasting models, have information asymmetry, have limited attention, and/or are affected by other psychological traits. To analyze whether the time-variation in disagreement is mostly representative of time-variation in the heterogeneity of agents' beliefs, or rather of time-variation in uncertainty I make use of the bi-directional relation between disagreement and volatility and the effect of disagreement on FX trading volume and liquidity. For the former, I utilize a standard VAR model, building on the proposition that the relation between uncertainty and volatility is mostly contemporaneous (volatility is often even used as a measure or proxy for uncertainty), and the relation between heterogeneity and volatility runs from the former to the latter (more

[5] Chapter 5 is based on "Ellen, ter S., W.F.C. Verschoor and R.C.J. Zwinkels (2015), Agreeing on Disagreement: heterogeneity or uncertainty in the foreign exchange market?, working paper."

heterogeneity induces more noise trading, which leads to higher levels of volatility). I also look into the (possibly time-varying) relation between disagreement and volume and disagreement and liquidity, thereby building on the proposition that there should be a positive relation running from heterogeneity (uncertainty) to volume (illiquidity) and vice versa. I further analyze whether disagreement has added value over realized volatility when linking it to risk and risk premium.

Finally, I will summarize and comment on the findings of the previous chapters in Chapter 6. I will conclude by giving my views on how to proceed in modeling, measuring, and utilizing heterogeneous beliefs in financial markets.

2 Heterogeneous beliefs in financial markets: an overview[6]

2.1 Introduction

This chapter provides an overview of a specific branch of the behavioral finance literature: heterogeneous agent models. The behavioral finance literature can be roughly divided into three strands. The first strand covers limits to arbitrage (De Long et al., 1990; Shleifer and Vishny, 1997) and focuses on the reasons for why arbitrage opportunities cannot always be exploited. The second strand models preferences, and models people's preferences in a more realistic way, such as in Kahneman and Tversky's 'Prospect Theory' (1979). The third strand covers non-rational beliefs, and is often associated with the literature on psychological heuristics and biases (Kahneman and Tversky, 1974; Hirshleifer, 2001).

In this overview we will not zoom into the different biases much, but will rather survey the empirical literature that acknowledges and incorporates the heterogeneous beliefs of financial market participants. More specifically, the focus is on the validation and estimation of (dynamic) heterogeneous agent models (HAM) that have their roots in the agent-based literature. This branch of behavioral finance assumes that agents are at least boundedly rational (Simon, 1975), and that they use certain rules of thumb in order to form expectations about future asset prices. This setup was first proposed by Zeeman (1974), and was further advanced by, among others, Frankel & Froot (1987), Chiarella (1992), Brock & Hommes (1997, 1998), Lux (1998) and De Grauwe & Grimaldi (2006). Although different names are being used in the literature for different forecasting strategies, they roughly come down to two or three types of agents. One typical type of agent uses past (price) information in order to predict future returns. The strategy this agent uses is referred to as (trend) extrapolation,

[6] This chapter is partly based on my master's thesis: "Ellen, ter S. (2010), Heterogeneous forecasting rules in the foreign exchange market: evidence from survey data, Erasmus University Rotterdam master's thesis."

technical analysis, bandwagon (for positive trend extrapolation), contrarian (for trend reversion) or *chartism*. The second type of agent bases his expectations on the deviation of the asset price from its fundamental value. This agent is said to be mean reverting, regressive or *fundamentalist*. Third or fourth types differ among studies and markets.

The purpose of this chapter is to give a comprehensive and extensive overview of the empirical work on heterogeneous agent models. Although several studies survey the theoretical work on this type of models (Hommes, 2006; LeBaron, 2000; Chiarella et al., 2009, among others), there is a gap in the literature when it comes to surveying empirical work. Although heterogeneous agent models perform very well in describing, explaining, and often forecasting (financial) markets dynamics, they are well-known to only a relatively small group of scholars. It is therefore important to summarize the overwhelming empirical support for these models, in order to show to the rest of the profession that these models are very successful and a promising alley for future research.

The remainder of this chapter is as follows. Section 2 gives a short description of how the field developed from rational agent models to models with boundedly rational agents. Section 3 summarizes the first theoretical contributions that have been made and some of the empirical support from experiments and survey studies. Section 4 gives an overview of the empirical work on heterogeneous agent models and the different types of estimation methods, and Section 5 concludes.

2.2 From rational expectations to bounded rationality

2.2.1 Efficient markets

Since the sixties, financial economists modeled financial markets based on assumptions of rationality of agents and efficient markets. In `Rational Expectations and the Theory of Price Movements' Muth (1961) states that "[expectations] are essentially the same as the predictions of the relevant economic theory". Fama (1965, 1970) further developed these implied assumptions from the `Efficient Markets Hypothesis' (EMH) in his famous work "Random Walks in Stock Market Prices", and they have been important building blocks for traditional finance theory ever since. Fama argued that financial markets are efficient because of rational behavior and -expectations of agents.

The assumption of rational agents implies that agents incorporate all available information in their decision-making process and that they are able to do this in an efficient way because they have full knowledge about the economic models underlying financial markets. This means that all agents should have the same expectations and that all prices of (financial) products should reflect their fundamental values. It is acknowledged that some agents might not be rational and that therefore mispricing may occur. However, the theory states that overreaction of some agents will be compensated by underreaction of other agents. Moreover, according to Friedman (1953), possible mispricing caused by so-called noise traders will soon vanish through the actions of rational agents. He argues that in such a way, speculators keep foreign exchange markets stable and efficient in case of a flexible exchange rate system.

The concept of arbitrage, as described by Friedman, is one of the main fundaments of the EMH. It entails that rational agents will observe mispricing and take actions upon it. Therefore, noise traders do not have a significant effect on prices, and it is impossible to consistently beat the market and earn riskless returns. In other words `there's no such thing as a free lunch'.

Although the efficient market hypothesis has been the conventional way of thinking about financial markets at least since the seventies, it has also been target of criticism since its publication. An important reason for the criticism is that the theory has some internal contradictions. If agents are rational and thus have the same expectations, there would be no trade in financial securities at all. With transaction costs taken into account and prices being perfect reflections of all (available) information no agent would either want to sell or buy its assets, since no extra returns can be made with that transaction. Milgrom and Stokey (1982) show that even when some agents have private information, this `no trade-theorem' applies. The fact that trade does take place, and in large and growing amounts, is one of the observations that weaken the EMH.

2.2.2 Limits of the EMH

Excessive trade (Milgrom and Stokey, 1982) is one of the anomalies that have caused a decline in the popularity of the Efficient Market Hypothesis. Other observed market anomalies that are difficult to explain in the conventional setup are, for example, momentum effect (Jegadeesh, 1990; on the short term recent losers tend to underperform the market, recent winners tend to outperform the market), post earnings announcement drift (Ball and Brown, 1968; prices do not adjust to information immediately but adjust slowly, causing a positive drift after positive news and a negative drift after disappointing news), long term reversal (De Bondt and Thaler, 1985; extreme past losers tend to outperform the market, past winners tend to underperform the market), size effect (Black et al., 1972; small firm stocks outperform stocks from large companies) and exchange rate puzzles (e.g. reversed evidence on purchasing power parity and interest parity).

Barberis and Thaler (2003) provide some more evidence on the statement that prices are not always right. They discuss mispricing in twin-shares (based on the Royal Dutch -- Shell Transport case, where the price ratio largely deviated from the equilibrium value), for stocks that get included in an important index (e.g. Yahoo stocks which rose 24% after being included in the S&P 500) and for internet carve-outs (where they use the example of the heavily underpriced 3Com). Since these cases of persistent mispricing show that seemingly riskless profit opportunities were not exploited by sophisticated investors they illustrate the frugalities of the Efficient Market Hypothesis.

One explanation for the persistence of mispricing that can be found in the literature is that there are serious limits to arbitrage. Among others, DeLong et al. (1990) explain why arbitrage opportunities cannot always be fully exploited. They argue that the existence of noise traders in the market brings along a significant amount of uncertainty that affects the riskiness of arbitrage. After all, if the effect of noise traders was strong enough to create the mispricing, these traders could as well increase the gap even further. Therefore noise traders can heavily destabilize the market. According to the EMH, mispricing cannot persist because it creates the possibility of a riskless return that would immediately be exploited. However, if the profit opportunity is not riskless because of the unpredictable behavior of noise traders, the mispricing can persist. This limit to arbitrage is usually labelled `noise trader risk', but there can be other risks that limit arbitrage opportunities.

Another limitation to arbitrage, described by Barberis and Thaler (2003) is fundamental risk. An arbitrage opportunity can be very risky if there is no perfect substitute security for the mispriced asset. An imperfect substitute asset is subject to idiosyncratic factors, which makes the opposite position in this security an extra risk factor. On top of that, the substitute security might be mispriced as well, which adds even more risk.

Besides the fact that arbitrage opportunities are not riskless, they are costly. The EMH leaves out both transaction and information costs. Acquiring information about mispricing is costly, but also exploiting arbitrage possibilities brings along significant costs like commissions and costs for borrowing stocks to be able to obtain a short position in specific securities. On top of that, regulators have imposed severe legal restrictions on investment constructions that involve short selling. In the words of Barberis and Thaler (2003): there is no free lunch if the prices are right, but this logic does not imply when reversed (i.e. the fact that there is no free lunch does not imply that prices are right).

Still, limits to arbitrage are no explanation of exchange rate puzzles, the inefficiency of markets and the inherent mispricing. After all, it does not explain how mispricing can occur in the first place. In the field of behavioral finance, the behavior of investors is evaluated and modelled using theories and experiment results from psychology and sociology. In such a way, economists get some insight in the non-rational beliefs and preferences of investors which may help to understand the anomalies we observe in financial markets.

Research on such non-rational preferences and beliefs in an economic setting was introduced by Kahneman and Tversky in the seventies. Their 1974 work on psychological biases that showed there is no such thing as a `homo economicus' has been very influential. Their work was mainly picked up in the eighties and nineties when more economists starting investigating the behavior of (financial) market participants. Some overview articles include Hirshleifer (2001) and Barber and Odean (2013). In 1979, they published a theory about decision making under risk, as an alternative to the `expected utility framework' that was extensively used before.

2.2.3 Survey evidence and bounded rationality

Although these contributions from the field of psychology are a great insight in the actual behavior of people and clearly show that agents do not behave in a rational way, they have generated quite some skepticism. After all, most economists already knew from the start that not all investors behave fully rational, but they saw it as a necessary assumption to be able to include investor behavior in their sophisticated economic models. They argued that behavioral economics and behavioral finance were impractical bifurcations of economics, since it was impossible to model the complex behavior of human beings. On top of that, the results from psychology were mainly generated by laboratory experiments which did not always replicate the real world in a very accurate way. These difficulties were reinforced by the problem that we could only observe price reactions to human behavior instead of observing the actual expectations.

The latter problem was partly overcome in the eighties, when companies like Money Market Services International (MMSI) and Consensus Economics started to gather investors' expectations of future asset prices by means of surveys. The use of survey data allows researchers to directly observe investors' expectations about future prices and exchange rates, therefore making it easier for them to test investor rationality and information efficiency and to detect possible expectation formation mechanisms that are used by institutional investors. One of the first authors that used survey data to test for rationality was Dominguez (1986). The author uses aggregated survey responses on exchange rates from MMS and finds that the null-hypothesis of unbiasedness can be rejected. Other papers (e.g. MacDonald and Marsh (1996); Cavaglia et al. (1993); Ito (1990); Frenkel et al. (2009)) confirm this result. Survey data therefore shows that investors are not fully rational.

Rationality within the Efficient Market Hypothesis roughly consists of two pillars: besides the unbiasedness assumption, we can also distinguish the assumption of efficient use of information. This entails that all investors use all available information as efficient as possible in forming expectations. Information orthogonality tests were also conducted by Dominguez in her 1986 paper. She showed that investors efficiently incorporate the information from past forecast errors in their expectation formation, but inefficiently use the information from the forward premium and leave out exogenous information, which is also confirmed by several follow-up studies. Cavaglia et al. (1994) find that the forward premium puzzle is caused by a combination of irrational traders and the existence of time-varying risk premia.

Because of the convincing evidence of non-rationality, it is of great interest to unravel the way agents behave and form expectations. Expectational mechanisms that are usually evaluated are mainly of the form of extrapolative, regressive and adaptive models. Extrapolative models generally have an autoregressive component: agents extrapolate historical movements into their expectations about the future. There is overwhelming micro-evidence that investors' expectations indeed have an extrapolative component (e.g. from surveys and experiments). Technical analysis is a form of extrapolation. Regressive models are in turn based on some reversion to the mean or a fundamental value of the asset, and adaptive models predict that agents adapt their expectations after they have made forecast errors in previous periods. Investigations of expectational mechanisms have shown that expectations for a period longer than 3 months ahead are stabilizing, while expectations for shorter periods ahead are destabilizing (Frankel and Froot, 1987, 1990; Cavaglia et al., 1993; Ito, 1990).

2.2.4 Boundedly rational heterogeneous agents models

Although survey studies provided evidence to reject the assumptions of rational expectation formation and information efficiency, the problem of modeling behavior persisted. As a response, some authors tried to stylize and model the behavior of investors, including some of the main biases. One of those models comes from Barberis et al. (1998). In their `model of investor sentiment' they include conservatism and representativeness to explain under- and overreaction of stock prices. Another response came from a new strand of behavioral finance theory in the form of boundedly rational heterogeneous agents models (BRHA models, or HAM). This heterogeneous agents theory, originally founded by Zeeman (1974), Beja and Goldman (1980) and Frankel and Froot (1987) and further developed by, among others, Brock and Hommes (1997, 1998), Day and Huang (1990), De Long et al. (1990a,b), Chiarella (1992), and De Grauwe et al. (1993), rejects the idea that investors behave rationally. Instead of focusing on the psychological microfoundations of behavioral finance like Barberis et al. (1998) do, they focus on modeling boundedly rational behavior (Simon, 1957).

With some exceptions, these investigations have in common that the distinction they make is one between a fundamental approach in forming expectations and an extrapolative approach, which is usually referred to as `technical analysis' or `chartist behavior'. Furthermore, some of the models assume that agents switch between the two strategies, depending on the forecasting performance or profitability of a certain strategy.

Fundamentalists base their expectations on economic theory. This group believes that the market price will revert to the intrinsic value of an asset and therefore bases expectations on the deviation of the market price from the fundamental value. Technical traders, or chartists, base their expectations on past price behavior. They extrapolate information from the past, expecting trends to continue in the same direction. Fundamentalist behavior is generally found to have a stabilizing effect on prices, while chartists tend to have a destabilizing effect driving asset prices away from the intrinsic value of the asset.

2.3 Early contributions and supporting evidence

2.3.1 Early contributions

One of the earliest examples of a heterogeneous agent model that we can find in the literature comes from Zeeman (1974). He is the first who recognizes and distinguishes two types of agents in the stock market, similar to the ones used in the BRHA models. One group, chartists, chases trends, therefore buying when prices go up and selling when prices go down. The other group, fundamentalists, is aware of the true fundamental value, and buys (sells) when the stock is currently undervalued (overvalued). Zeeman explains the slow feedback flow observed in the stock market by the fact that the rate of change of stock market indices responds to chartist and fundamentalist demand faster than their demand responds to the return changes of these indices. In other words, while chartists and fundamentalists demand has a direct effect on returns, fundamentalists may only start selling when a stock is overvalued by a certain amount, thereby causing bull (chartists driving the price up) and bear (both chartists and fundamentalists selling stocks) markets. Although Zeeman's model is very similar in terms of set-up and implications to the BRHA models as we know them now, it lacked clear micro-foundations (Hommes, 2006) and his theory was not picked up in the seventies.

Another important contribution came from Beja and Goldman (1980). According to them it is obvious that a man-made market where people interact and respond to each other cannot be fully efficient. Therefore, discrepancies will exist and human beings will naturally respond to these discrepancies by speculating on their expected direction of the market. Since this is bound to lead to different price dynamics than would occur under the efficient markets hypothesis they propose an alternative theory. In line with Zeeman (1974), Beja and Goldman assume a mechanism where the speed of price changes and the speed of demand changes are not in line. Furthermore, they propose a market which consists of fundamental (based on expectations of future equilibrium prices) demand and speculative (based on the state of the market) demand. Dynamics in the aggregate demand especially occur due to relative sizes of the fundamental and speculative demand (which becomes larger if the price change is larger than expected) and the flexibility of the trend followers. The market will be stable if the impact of the fundamental demand is sufficiently high or if the impact of the trend followers is sufficiently low.

The heterogeneous agents literature has thereafter benefitted a lot from contributions from, among others, Frankel and Froot (1987, 1990a,b), DeLong et al. (1990b), and Brock and Hommes (1997, 1998). Frankel and Froot showed, by using survey data, that expectations could be classified as extrapolative, regressive, and adaptive (1987), or as chartist and fundamentalist (1990a). Brock and Hommes (1997, 1998) introduced an intuitive switching rule, effectively implying that investors would switch to the rule with the best recent performance. HAM have been very well able to explain and replicate certain stylized facts of financial markets (Lux, 2009), such as volatility clustering, fat tails, and bull and bear markets. For comprehensive overviews of the (theoretical) HAM literature, see for example Hommes (2006), Chiarella (2009), and LaBaron (2000).

2.3.2 Supporting evidence on micro-level

Over the years studies have collected empirical evidence in favor of the chartist-fundamentalist approach in various ways. As the models are agent-based, there is evidence confirming the behavior of the market participants on micro-level. However, the models have clear implications for the dynamics of the markets in which these agents participate. This means that there is also supporting evidence on macro-level, confirming the ‘behavior’ of markets. In this section we will discuss some of the evidence collected on micro-level, of which the majority comes from laboratory experiments and survey studies.

Schmalensee (1976) was one of the first to use experimental methods to reveal expectation formation processes for time series, in particular with respect to technical rules. Smith et al. (1988) are able to replicate bubbles and crashes within laboratory experiment expectations. De Bondt (1993) and Bloomfield and Hales (2002) use classroom experiments and find evidence of trend-following behavior, where Bloomfield and Hales (2002) also find support for the assumption in Barberis et al. (1998) that investors perceive past trend reversals as an indicator for the probability of future reversals even though they are aware of the random walk character. A laboratory experiment is used by Hommes et al. (2005) to evaluate how subjects form expectations when all they know is dividend yield, interest rates and past realized prices. The authors find that participants make use of very similar linear rules, such as autoregressive or adaptive strategies, in forming expectations.

As (laboratory) experiments are, in general, not fully able to replicate the real world situation, and the generalizability has, therefore, been questioned, attempts have been made to directly measure investor expectations and expectation formation rules. To this end, both quantitative and qualitative surveys have been conducted. Taylor and Allen (1992) show, based on a questionnaire survey, that 90% of the foreign exchange dealers based in London use some form of technical analysis in forming expectations about future exchange rates, particularly for short-term horizons. The foreign exchange dealers further expressed that they see fundamental and technical analyses as complementary strategies for making forecasts and that technical analysis can serve as a self-fulfilling mechanism. Menkhoff (2010) gathered similar data from fund managers in five different countries. In line with the findings of Taylor and Allen, they find that 87% of the fund managers they survey uses technical analysis. About 20% of the fund managers considers technical analysis as more important than fundamental analysis.

Various quantitative surveys have been evaluated as well. For a more extensive overview, see Jongen et al. (2008). Frankel and Froot (1987, 1990, 1991) have had a great impact on the foreign exchange literature and the further development of heterogeneous agent models. They were among the first to show that survey data reveals non-rationality and heterogeneity of investors. They also find evidence for the chartist-fundamentalist approach employed in many of the heterogeneous agent models. Others have confirmed these findings in later years, and with various datasets. Dick and Menkhoff (2013) use forecasters' self-assessment to classify themselves as chartists, fundamentalists, or a mix. They find that forecasters who classify their forecasting tools as chartist use trend-following strategies and who classify as fundamentalist have a stronger behavior toward purchasing power parity. They also find that chartists update their forecasts more frequently than fundamentalists.

Ter Ellen et al. (2012) are among the first to estimate a dynamic heterogeneous agent model on survey data, meaning that the expectations of investors can be dynamic in various ways. They find that three forecasting rules fit the survey data very well: a PPP rule (fundamentalist), a momentum rule (chartist) and an interest parity rule. They confirm the earlier finding from Frankel and Froot (1990, 1991) that investors use more speculative strategies for shorter horizons (1 month) and more fundamental strategies for longer horizons (12 months). Moreover, investors switch between forecasting rules depending on the past performance of these rules. Goldbaum and Zwinkels (2014) find that a model with fundamentalists and chartists can explain the survey data well. As in Ter Ellen et al. (2012), they find that fundamentalists are mean reverting and that this model is increasingly used for longer horizons. Chartists have contrarian expectations. A model with time-varying weights on the different strategies outperforms a static version of this model.

Jongen et al. (2012) also allow the weights on different strategies to vary depending on market circumstances. However, instead of directly explaining the survey expectations, they analyze the dispersion between forecasts. They find that the dispersion is caused by investors using heterogeneous forecasting rules and having private information. This is in line with the earlier findings of Menkhoff et al. (2009) for a dataset on German financial market professionals.

Zwinkels and co-authors have collected evidence for heterogeneous beliefs from data on fund managers' exposure. Verschoor and Zwinkels (2013) show that foreign exchange fund managers behave like heterogeneous agents. They find that fund managers allocate capital to a momentum, carry, and value strategy depending on the past performance of these strategies. They make money by employing a negative feedback strategy: shifting money from recent winning strategies to recent losing strategies. Schauten et al. (2011) apply a heterogeneous agent model to hedge fund risk exposure. Because of the non-linear trading strategies that hedge fund managers employ, a non-linear model with dynamic weights seems to be appropriate to capture the hedge fund risk exposure. The heterogeneity of the hedge funds lies in the dynamic weighing of exposure to different risk factors

2.3.3 An example

We will now provide an example of a heterogeneous agent model with chartists, fundamentalists, and dynamic weighting of the two groups. Many of the models employed can be simplified to this model. The form of the model we show here is mostly related to some of our own applications of HAM (e.g. De Jong et al., 2010; Ter Ellen and Zwinkels, 2010; Chiarella et al., 2014b), which are largely based on the functional form from Brock and Hommes (1997, 1998).

The base of the model is the price of an asset. The price of an asset tomorrow, P_{t+1}, equals the price of today, P_t, and the weighted demand of different types of agents, typically chartists and fundamentalists:

$$P_{t+1} = P_t + W_t\, D_t^c + (1 - W_t)\, D_t^f \tag{2.1}$$

Here, W_t is the chartist weight in the market, D_t^c is the chartist demand, $(1 - W_t)$ is the weight of fundamentalists in the market, and D_t^f is the demand function of fundamentalists. The demand functions can be specified as the difference between the current asset price and the expected asset price under chartist ($E_t^c[P_{t+1}]$) or fundamentalist ($E_t^f[P_{t+1}]$) expectations:

$$D_t^c = a^c(E_t^c[P_{t+1}] - P_t) \tag{2.2}$$

$$D_t^f = a^f(E_t^f[P_{t+1}] - P_t) \tag{2.3}$$

The demand is naturally positively related to the expected price change for both chartists and fundamentalists. In other words, when agents expect the price to increase in the coming period, they will increase their demand for that asset today. However, chartists and fundamentalists differ in the way they form expectations about future prices. Chartists form their expectations based on some form of technical analysis. Commonly used rules are moving average (MA) rules and AR(n) rules. For simplicity we will focus on a simple AR(1) rule for chartists:

$$E_t^c[P_{t+1}] = P_t + \beta_c(P_t - P_{t-1}) \tag{2.4}$$

According to this rule, chartists expect price movements to continue if $\beta_c > 0$ or to reverse if $\beta_c < 0$. This often depends on the time horizon, i.e. whether t denotes a week, month, or year, for example.

Fundamentalists form their expectations based on their perception of a fundamental value of the asset, $\overline{P_t}$, and the current price deviation thereof:

$$E_t^f[P_{t+1}] = P_t + \beta_f(\overline{P}_t - P_t). \tag{2.5}$$

Often fundamentalists are a stabilizing force, which means they expect prices to revert back to their fundamental levels. In such a case $\beta_f > 0$. The expected speed of reversion in periods can be calculated by $\frac{1}{\beta_f}$. Often, computing a fundamental value as input for the model is one of the most challenging tasks of estimating a HAM. For some markets there are multiple competing models, for example in the foreign exchange market (PPP, UIP, monetary model, …), at other times there are no obvious candidates at all (for example in commodity markets).

In many applications, the dynamics of the market can be best explained with time-varying weights for chartists and fundamentalists (in other words, when agents can 'switch' between the strategies). Switching functions may vary. For an evaluation of different switching functions, see Baur and Glover (2014). The example we show is an adapted multinomial logit rule from Brock and Hommes (1997, 1998) and similar to Ter Ellen and Zwinkels (2010) and Chiarella et al. (2014).

In this case, the weight of the chartists depends on the recent forecasting accuracy of the chartist forecasting rule, π_t^c, relative to the recent forecasting accuracy of the fundamentalist rule, π_t^f:

$$W_t = \left[1 + exp\left(\gamma\left[\frac{\pi_t^c - \pi_t^f}{\pi_t^c + \pi_t^f}\right]\right)\right]^{-1} \tag{2.6}$$

In this setup W_t is the proportion of chartists in the market (or the weight put on the chartist forecasting rule), and $1 - W_t$ is the proportion of fundamentalists. The forecasting accuracy of chartists (fundamentalists) is measured as the mean squared error of the chartists (fundamentalists) over the past period. Note that it is also possible that the agents evaluate the rule over more than one period.

$$\pi_t^c = [(E_{t-1}^c[P_t] - P_{t-1}) - \Delta P_t]^2 \tag{2.7}$$

$$\pi_t^f = [(E_{t-1}^f[P_t] - P_{t-1}) - \Delta P_t]^2 \tag{2.8}$$

As in Ter Ellen and Zwinkels (2010) and Chiarella et al. (2014), equation (2.6) differs slightly from the weighting mechanism originally proposed by Brock and Hommes (1997). Instead of using the absolute difference in forecasting accuracy of the two rules, $\pi_t^c - \pi_t^f$, weights are calculated by using the relative forecasting (in)accuracy ($\frac{\pi_t^c - \pi_t^f}{\pi_t^c + \pi_t^f}$). Ter Ellen and Zwinkels (2010) argue that this method has the advantages of ease of estimation and comparability between different markets. The coefficient γ is called the intensity of choice and represents the investors' speed of switching[7]. If $\gamma = 0$, investors do not adapt the importance given to the two rules and $W_t = 0.5$. The other extreme is when $\gamma = \infty$ where investors are perfectly adaptive and immediately adjust all weight to the rule with the smallest forecast error. A small positive γ can be an indication of status quo bias, introduced by Kahneman et al. (1982). If investors suffer from this bias, they are reluctant to change their status quo belief, which results in slower updating of beliefs.

2.4 Estimation

Due to the complex and nonlinear nature of the bounded rationality heterogeneous agent models, most of the early papers in this field were restricted to theoretical explanations and simulations of these models. These simulations produced interesting results and were able

[7] Or, in essence, the flexibility of an investor to change weights on the two respective trading rules.

to reproduce many of the stylized facts observed in (financial) markets. However, it was not clear whether these outcomes resulted from the strength of the model or from the choice of parameter values. Therefore, direct confrontation of the model with real financial data was desirable. Vigfusson (1997) was the first to make an attempt to estimate the parameters of a model with chartists and fundamentalists to financial data. Given that the dynamic weighting of the two strategies is unobserved, Vigfusson applied the Markov regime switching approach to the foreign exchange market, where chartist and fundamentalist behavior can be seen as different states. After him, several other authors used this approach for the foreign exchange market (Ahrens and Reitz, 2005) and the stock market (Alfarano et al., 2005, 2006; Chiarella et al., 2012). Baak (1999) and Chavas (2000) suggested an approach with General Method of Moments (GMM) and Kalman filtering to estimate a chartist-fundamentalist model for the beef market. Not much later, Winker and Gilli (2001, 2003) used a simulation based indirect estimation approach by minimizing loss functions based on the simulated moments and the realized moments from foreign exchange data. Westerhoff and Reitz (2003, 2005) incorporated dynamic weighting in one of the two types of agents by means of a STAR GARCH estimation for the foreign exchange market (2003, time-varying fundamentalist impact) and the commodity market (2005, time-varying chartist impact). Manzan and Westerhoff (2007) also apply this method with time-varying weights on the chartist impact for the foreign exchange market, whereas Reitz and Slopek (2009) apply it to the oil market.

An important contribution in the estimation of heterogeneous agents models came from Boswijk et al. (2007). They use nonlinear least squares estimation combined with a multinomial logit switching rule to empirically validate a heterogeneous agents model for the S&P 500. The main improvements of their method over estimating based on Markov switching are the smaller number of parameters to be estimated and the deterministic nature of their switching process, in contrast to a stochastic Markov process. Many empirical papers on heterogeneous agents models have successfully used the techniques from Boswijk et al. (2007) for stock markets (De Jong et al., 2009; Chiarella et al., 2014a) and foreign exchange markets (De Jong et al., 2010), but also for less obvious asset classes, such as oil (Ter Ellen and Zwinkels, 2010), housing (Kouwenberg and Zwinkels, 2014), gold (Baur and Glover, 2014), options (Frijns et al., 2010) hedge funds (Schauten et al., 2011), and credit markets (Chiarella et al., 2014).

2.4.1 Choice of estimation method

2.4.1.1 Markov switching

Vigfusson (1997) was the first in attempting to estimate a chartists and fundamentalists (c&f) model similar to the one described in Frankel and Froot (1987). Because the dynamic weighting of the two strategies is unobservable, he uses a Markov regime switching approach, where chartist and fundamentalist behavior can be seen as two different states. Ahrens and Reitz (2005) follow Vigfusson (1997) by taking a regime switching approach to estimate a heterogeneous agent model with chartists and fundamentalists. Similarly, Alfarano et al. (2005, 2006) use Markov switching. They recognize the complexity of the agent based models and the fact that this makes them difficult to directly estimates the underlying parameters. They simplify the model to a closed-form solution for returns to overcome this problem. Although their model is highly simplified compared to some of the earlier agent-based models for financial markets, the authors are still able to reproduce some of the stylized features of stock returns. The two groups of traders are labeled as fundamentalists and noise traders, and switching between the two groups occurs based on asymmetric switching probabilities, inspired by Kirman's herding mechanism. The switching is asymmetric because the transition probability of an agent switching from the group of noise traders to the group of fundamentalists differs from the transition probability of a switch in the opposite direction. Chiarella et al. (2012) use Markov regime switching to explain the market dynamics of the S&P500. In their model, investors' beliefs about returns are regime dependent, and regimes (a bull state of the market with positive returns and low volatility or a bust state of the market with negative returns and high volatility) are generated by a stochastic process.

2.4.1.2 Indirect and optimization estimation techniques

Baak investigates whether a bounded rationality model has added value compared to a model with only rational agents. He tries to detect bounded rationality in the beef cattle market by converting the model in an optimal regulator problem with distortions and using

Kalman filtering. The model he uses is a version of a rational agents model, extended with a fixed proportion of boundedly rational agents who base their expectations on time series observations. Baak finds that the extended model has a better fit than the original rational agents model. Chavas (2000) uses General Method of Moments (GMM) to detect heterogeneity and to measure the size of groups with different levels of rationality for the US beef market. One of the main drawbacks of these papers is that in the models used there is no time variation in the market composition. Franke (2009) estimates the parameters of a heterogeneous agent model by applying the simulated method of moments. He finds that, when using an adjusted weighting function in the objective functions, the models parameters are economically and statistically satisfactory. Not all papers on HAM estimation are positive about the use and appropriateness of such models. Amilon (2008) uses maximum likelihood and efficient method of moments and finds that the models generally have a poor fit and do not generate all the stylized facts that some of the simulation studies are able to match.

Both papers of Gilli and Winker (2001, 2003) use a simulation based indirect estimation approach to find the parameter values of a heterogeneous agent model applied to the US Dollar - German Mark exchange rate. The parameter values of the model are obtained by minimizing a loss function based on the model simulated moments and the moments from the real data. The 2001 paper serves as an introduction of this method and therefore only focuses on two moments: kurtosis and ARCH-effects. The authors only estimate the random switching probability parameter and the probability that an agent will switch after interacting with another agent. In the 2003 paper, the optimization algorithm is improved and a third parameter, the standard deviation of noise in the majority assessment, is estimated.

2.4.1.3 STAR GARCH

Westerhoff, Reitz and Manzan use a STAR-GARCH approach in several papers. An important characteristic of this estimation technique is that only one type of agents can have a deterministic time-varying weight. Westerhoff and Reitz (2003) estimate a STAR GARCH model where the impact of fundamentalists depends on the strength of their belief in fundamental analysis. If the misalignment of the exchange rate with the fundamental value increases, fundamentalists lose their faith in fundamental analysis and leave the market. In their 2005 paper they estimate a model for the US corn market with constant stabilizing fundamentalist behavior and dynamic technical trading activity, which is time-varying depending on the misalignment of the corn price. Manzan and Westerhoff (2007) estimate a heterogeneous agent model with nonlinear time variation in the chartists' extrapolation rate (similar to the model of Westerhoff and Reitz, 2005) on five major currencies against the US dollar. Whereas fundamentalists have a constant belief about the exchange rate misalignment (the difference between the spot rate and the PPP rate), namely that it will decrease, chartists expect trends to continue when the absolute change is below a certain threshold band and expect mean reversion beyond that threshold (unlike the chartists in Westerhoff and Reitz (2005), who become more active the larger the misalignment is).

2.4.2 Full switching models

2.4.2.1 Stock market

Nowadays, the most popular method of estimating a heterogeneous agents model is with nonlinear least squares or maximum likelihood, combined with a multinomial logit switching rule which is inspired by the work of Brock and Hommes (1997,1998). This method was introduced by Boswijk et al. (2007), who directly estimate a BRHA model on stock returns (S&P 500). In their model there are heterogeneous agents with access to the fundamental value of a risky asset, but with different beliefs about the persistence of the deviation between the spot price and the fundamental price of the asset. Switching between the different beliefs takes place based on the relative past profitability of that strategy. Chiarella et al. (2014) estimate a heterogeneous agents model for the S&P500 with three types of agents: fundamentalists, chartist and noise traders. Consistent with most of the other empirical studies, fundamentalists are stabilizing with respect to the fundamental value of the asset. Chartists trade based on a moving average rule given by a geometric decay process, whilst most empirical studies rely on an AR(1) rule. The relative weight of fundamentalists and chartists in the market changes over time based on the relative performance of these rules, the impact of noise traders is assumed to be constant. Noise traders have no specific expectations of future returns, their demand is driven by a noisy signal that depends on volatility. De Jong et al. (2009) also distinguish three types of agents, to shed light on the Asian crisis in the context of heterogeneous agents. Besides chartists and fundamentalists, they distinguish internationalists, who condition their expectations on foreign market conditions. In a two-country model (with Hong Kong and Thailand) for the stock market, chartists and fundamentalists base their expectations on past price changes and the price deviation from the fundamental value, respectively, whereas internationalists base their expectations on the past price changes of the foreign market. Market dynamics occur due to switching between the different groups conditional on their past forecasting performance. Their estimation method is in many ways comparable to the one in Boswijk et al. (2007), yet De Jong et al. use maximum likelihood techniques instead of nonlinear least squares. All these studies compute a fundamental stock price by taking the discounted value of expected future dividends, which comes down to a simple Gordon growth model when a constant growth rate of dividends is assumed.

2.4.2.2 Foreign exchange market

De Jong et al. (2010) estimate a full heterogeneous agents model with switching on exchange rates. By estimating the chartist-fundamentalist model on EMS rates, they circumvent the problem of having to choose a fundamental rate. Instead, they can use the `parity' rate. With a survey dataset from Consensus Economics London, Goldbaum and Zwinkels (2014) directly test investor heterogeneity and expectation formation for the Japanese yen and the Euro against the U.S. dollar. The authors estimate three different models with chartists and fundamentalists. In the first model, both rules are estimated for the full sample of respondents and time. In the second model, every forecaster is labeled as being either fundamentalist or chartist, based on the sum of the relative difference between the forecast and the outcome of the respective forecasting strategy. Finally, the respondents are allowed to switch their strategy. Every single forecast is labeled as resulting from either the fundamentalist or chartist strategy. The authors use the monetary model to compute a fundamental value for the exchange rates. Another paper that evaluates investor expectations for the foreign exchange market with survey data comes from Ter Ellen et al. (2011). They estimate a full heterogeneous agent model with dynamic weights of PPP traders (fundamentalists), momentum traders (chartists) and interest parity traders on forecasts for the Euro, Great Britain pound and Japanese yen against the U.S. dollar and the Japenese yen against the Euro.

2.4.2.3 Other asset classes

Where Reitz and Slopek (2009) take a STAR-GARCH approach with heterogeneous agents to explain large oil price swings, ter Ellen and Zwinkels (2010) employ maximum likelihood with a multinomial logit switching rule. In their approach, the market impact of trend extrapolating chartists and mean reversion fundamentalists is time varying, based on the relative past forecasting accuracy of the strategies. Fundamentalists believe in mean reversion of the WTI and Brent price of crude oil to a long term moving average of the oil price, whereas chartists extrapolate the price movement from the previous period. Considering that there is no concensus on the fundamental value of oil and computing one can be costly, the authors use a two-year moving average as a proxy for the fundamental value.

Frijns et al. (2010) propose a way to model heterogeneous expectations of volatility by applying a heterogeneous agent model to the option market, where volatility is priced and traded. Fundamentalists believe that conditional volatility will revert to the level of the unconditional volatility and chartists trade based on recently observed unexpected shocks. Their heterogeneous agent model simplifies to a GJR-Garch(1,1) model with time-varying coefficients, which depend on the time-varying market impact of chartists and fundamentalists.

Kouwenberg and Zwinkels (2014) show that even the price movements in the U.S. housing market can be well explained by a dynamic heterogeneous agent model. The model is estimated with maximum likelihood, including fundamentalists who believe in mean reversion of housing prices to a rents-based fundamental value and chartists who destabilize the market by extrapolating trends. Agents switch between strategies based on the past forecasting accuracy of the respective strategies.

2.4.3 Behavior of chartists and fundamentalists

Most empirical studies on BRHA models use the classification of chartists and fundamentalists as found in the theoretical literature, where chartists either base their expectations on an autoregressive or moving average rule, and fundamentalists choose a fundamental value that is appropriate for the asset class under consideration. According to the theory on chartists and fundamentalists, chartists are generally destabilizing by extrapolating and enforcing trends, whereas fundamentalists have a stabilizing impact on the asset price due to their mean reverting expectations. This presumption is confirmed by many empirical validations of the model. Both Boswijk et al. (2007) and Chiarella et al. (2014a) find support for mean reversion in fundamentalists' expectations and trend extrapolation in chartists' expectations of the S&P500. The model with time-varying weights has a significantly better fit than the static model. Lof (2014) also estimates a heterogeneous agent model on S&P500 data. The types of agents he distinguishes are fundamentalists, rational speculators and contrarian speculators. The latter two types have exactly opposing beliefs to one another. He finds that the existence of contrarians can explain some of the most volatile episodes of the S&P500.

Similar results are found for commodity markets. Westerhoff and Reitz (2005) find that chartists are highly stabilizing, and that this effect becomes stronger the further the price of corn is away from its fundamental, or long-run equilibrium, price. Reitz and Slopek (2009) explain the large price swings observed in the oil market by stabilizing fundamentalists, who have a larger impact the larger the misalignment of the oil price is, and chartists, who are dominant and destabilizing when the price of oil is close to its fundamental value. Ter Ellen and Zwinkels (2010) confirm the destabilizing (stabilizing) effect of chartists (fundamentalists) in the WTI and Brent markets for crude oil. They also find asymmetry in the responses of both chartists and fundamentalists. Furthermore, high weights for the chartist strategy coincide with different price spikes in the sample period, suggesting that they contributed to an oil price bubble in these periods. The model has a good out-of-sample fit. The authors show that the heterogeneous agent model outperform the random walk model and a VAR(1,1) model. Baur and Glover (2014) find that investors in the gold market are heterogeneous. However, the coefficients they obtain for chartist and fundamentalist behavior are quite different from what is commonly found in other financial markets.

Results for the foreign exchange market are not that consistent. Manzan and Westerhoff (2007) find that for a large number of currencies against the U.S. dollar, fundamentalists are increasingly stabilizing for a larger misalignment of the exchange rate. However, chartists are destabilizing only within a certain range. When the past appreciation or depreciation of the exchange rate is larger than the threshold value, their behavior becomes stabilizing. De Jong et al. (2010) find evidence of stabilizing behavior of all types of agents for EMS rates, a result they assign to the investors' trust in the monetary authorities. Westerhoff and Reitz (2003) find less optimistic results for The U.S. dollar against the British pound, German mark and Japanese yen. In their model, fundamentalists lose their faith in fundamental analysis if the misalignment of the exchange rate with the fundamental value increases, and leave the market. Therefore the dynamics in the fundamentalists' behavior further destabilize the exchange rate. Another remarkable outcome is found by Vigfusson (1997). His results show that periods of stability in the CAN$/US$ exchange rate correspond to high probabilities of being in the chartist regime (based on the moving average rule). The opposite effect is observed for the autoregressive chartist rule.

The evidence in favor of heterogeneous agents extends more and more to other (financial) markets. Frijns et al. (2010) estimate a heterogeneous agent model on the option market, where investors have heterogeneous expectations about the future level of volatility. They confirm the presence of different types of traders in that market. Kouwenberg and Zwinkels (2014) show with their HAM estimation for the U.S. housing market that the dominance of chartists in the housing market from 1992 to 2005 can explain the bubble-like behavior of housing prices in that period. Their model with time-varying impact of fundamentalists, who believe in mean reversion to a fundamental value based on rents, and chartists, who extrapolate past price trends, explains the housing price for the in-sample period, and is also able to predict the decline in housing prices from 2006 onwards. Chiarella et al. (2014) analyze the large deviations from fundamental levels of credit risk for some European countries during the European sovereign debt crisis and find that these can be partly explained by a combination of increased global risk aversion and the dynamics between momentum traders (chartists) and fundamentalists.

2.5 Conclusion

Although the rational paradigm has been at the forefront of financial markets research since the seventies, rejections of this paradigm and attempts to model investor behavior in a different way are gaining ground. Boundedly rational heterogeneous agent models (HAM) are an example of such models. In this chapter I have provided an overview of papers estimating such models and their main results.

Heterogeneous agent models typically explain the stylized facts of financial markets well, and they are able to replicate important episodes of turmoil. Nevertheless, work on these models rarely appears in general economics and finance journals. This may be partly explained by the terminology used in this niche of behavioral finance. After all, the applications that do get attention from such journals generally use a different terminology, such as ‘momentum’ instead of ‘chartist’. To grow further from a niche model to a generally accepted subject, adapting the terminology used in these models may be the way forward.

3 Dynamic expectation formation in the foreign exchange market[8]

3.1 Introduction

Several foreign exchange market anomalies (e.g. excessive trade, momentum, forward premium puzzle) cannot be fully explained within the traditional framework. Also, non-fundamental strategies such as carry trade (Menkhoff et al., 2012a) and momentum (Menkhoff et al., 2012b) can be profitable. In addition, there is ample evidence of investors having expectations that are non-rational in the traditional sense, and also heterogeneous (Ito, 1990; Cavaglia et al., 1993; MacDonald and Marsh, 1996; Menkhoff et al., 2009; Jongen et al. 2012). Several approaches have been suggested in the literature to address these issues. For example, the scapegoat approach (Bacchetta and van Wincoop, 2009; Sarno and Valente, 2009) assumes that exchange rates can be explained by varying fundamentals over time. The learning approach (see e.g. Markiewicz, 2012 and Markiewicz and De Grauwe, 2013) poses that agents in the foreign exchange market behave as econometricians and attempt to learn the true data generating process from the empirical data. In this chapter, we follow the behavioral finance literature and use survey data to test whether expectations are formed using heuristics, and whether the use of these heuristics is time-varying following the theoretical work of De Grauwe and Grimaldi (2006) and Spronk et al. (2013).

[8] This chapter is based on "Ellen, ter S. (2010), Heterogeneous forecasting rules in the foreign exchange market: evidence from survey data, Erasmus University Rotterdam master's thesis." and "Ellen, ter S., W.F.C. Verschoor and R.C.J. Zwinkels (2013), Dynamic expectation formation in the foreign exchange market, Journal of International Money and Finance." We would like to thank the editor, an anonymous referee, Alessandro Beber, seminar participants at the Tinbergen Institute and Erasmus Research Institute of Management (ERIM), and participants of the 2011 meeting of the Society of Nonlinear Dynamics and Econometrics (SNDE), the 3rd EMG Conference on Emerging Markets Finance, the 16th Annual Workshop on Heterogeneous Interacting Agents (WEHIA), the 2011 meeting of the European Economic Association (EEA) and the 2011 PREBEM Conference.

The assumption of rational market participants with homogeneous expectations, once firmly rooted in financial theory, is losing ground in favor of alternative assumptions of agent behavior such as bounded rationality and heterogeneous expectations. Bounded rationality of market participants was already introduced by Simon in 1957. In this framework it is assumed that agents are boundedly rational and that they use certain rules of thumb, heuristics, to form expectations about future asset prices. Various attempts have been made to determine what these rules of thumb are and how they are being used, ranging from theoretical models to lab experiments and survey analyses.

The main theoretical contributions come from Frankel and Froot (1987b), De Long et al. (1990) and Lux (1998). Frankel and Froot (1987b) develop a model with three types of actors: chartists ('trend followers'), fundamentalists ('model followers') and portfolio managers. The portfolio manager is the only actor who buys and sells assets, and he receives input from the two other types. Therefore, he makes trades that can be seen as a weighted average between the chartist and the fundamentalist expectations. Lux' (1998) also makes this distinction between chartist and fundamentalist strategies. De Long et al. (1990) make a distinction between noise traders and sophisticated traders. In this model, the noise traders create a risky investment environment and are able to obtain excess returns without having access to inside information. Because of the presence of this group in the market, prices can deviate significantly from their fundamental value for longer periods of time. All of these authors explain various market anomalies and stylized facts with their models of investor behavior.

The presence and behavior of different types of agents in financial markets has been examined in a number of ways. Schmalensee (1976) was one of the first to use experimental methods to reveal expectation formation processes for time series, in particular with respect to technical rules. De Bondt (1993) and Bloomfield and Hales (2002) use classroom experiments and find evidence of trend-following behavior, where Bloomfield and Hales (2002) also find support for the assumption in Barberis et al. (1998) that investors perceive past trend reversals as an indicator for the probability of future reversals even though they are aware of the random walk character. Hommes et al. (2005) illustrate coordination of expectations among participants in an experimental setting.

As an alternative method to measure expectations, attempts have been made to directly measure investor expectations and expectation formation rules. To this end, both quantitative and qualitative surveys have been conducted. Taylor and Allen (1992) show, based on a questionnaire survey, that 90% of the foreign exchange dealers based in London use some form of technical analysis in forming expectations about future exchange rates, particularly for short-term horizons. The foreign exchange dealers further expressed that they see fundamental and technical analyses as complementary strategies for making forecasts and that technical analysis can serve as a self-fulfilling mechanism. Various quantitative surveys have been evaluated as well (among others, Ito, 1990; Cavaglia et al., 1993; MacDonald and Marsh, 1996; Branch, 2004; Menkhoff et al., 2009). They all find heterogeneity in expectations, and most of them attribute this to extrapolative, regressive and adaptive expectations (for an overview, see Jongen et al., 2008). However, all these studies assume static and non-time-varying expectation formation.

Branch (2004), investigates inflation expectations and finds that agents switch between different exogenously determined forecasting techniques (VAR, naïve and adaptive) based on the mean squared prediction errors of the strategies. This chapter extends Branch (2004) by introducing dynamics in expectation formation strategies for financial markets, being the foreign exchange market, where feedback effects from expectations to realizations can be stronger than in the case of inflation. In addition, the forecasting rules are estimated endogenously. Whereas Branch (2004) optimizes the forecasting rules exogenously on realized inflation, we estimate the forecasting rules endogenously on the survey expectations. This approach allows for more flexibility in results as it does not presume consistency between expectations and realizations.

In this chapter we will further investigate this heterogeneity by testing three well-known foreign exchange forecasting strategies on a survey dataset with forecasts from foreign exchange analysts and large international banks. These strategies can be summarized as a momentum rule, a PPP rule and an interest parity rule. The choice for these three strategies is motivated partly by the academic literature on exchange rates and heterogeneous agents (see Spronk et al., 2013) and partly by evidence from industrial practice (see Pojarliev and Levich, 2008, 2010).

We will advance the study of different types of agents in two ways. First, we introduce dynamics in the strategies by distinguishing between time-varying bandwagon versus contrarian expectations in the momentum strategies and by distinguishing between carry trade versus UIP expectations. Although, in general, it is acknowledged that the existence of such opposing beliefs could be hidden on an aggregated level because they even out, the distinction has, to the best of our knowledge, never been made when working with empirical data. Secondly, we will increase the dynamic nature of the model by allowing the agents to switch between different strategies based on forecasting accuracy with respect to the market exchange rate. These two additions, combined with the survey dataset, allow us to evaluate different currencies as well as different forecast horizons. Furthermore, the dataset has never been used for this purpose[9], thus making this chapter a valuable extension to the existing literature on behavioral finance, expectation formation, exchange rate dynamics and survey data.

We find evidence for the existence of all three strategies both when tested separately and when tested in a combined model, indicating that agents use these different strategies to form expectations about future returns. Moreover, we find dynamics in expectation formation in three different ways. First, agents hold opposing beliefs within different strategies and change these beliefs over time. Secondly, expectation formation is dynamic in the sense that the expectation formation rules change for different forecasting horizons. Carry trading and momentum are the main applied strategies for short-term forecasting, whereas PPP and UIP are predominantly used for long-term forecasting. Finally, the results show that agents attach time-varying weights to the different strategies based on the past performance of the strategies, especially for the long run forecast horizons.

The remainder of this study is organized as follows. In Section 2, we describe the dataset, Section 3 contains the methodology used, and Section 4 contains the results. In Section 5, we give some concluding remarks and suggestions for further research.

[9] It has been used by Sarno and Sojli (2009) for an empirical investigation of the link between fundamentals and exchange rates.

3.2 Data

To get a better understanding of the expectation formation process of agents, we use a dataset of investor expectations. The dataset that is central to this work is a survey dataset from FX Week[10,11], which contains forecasts at the weekly frequency from a large number of wholesale investors for several exchange rates and forecast horizons. The names of the respondents are revealed and include JPMorgan, Barclays Capital, Citigroup, RBS and Société Générale. Anecdotal evidence suggests that sell-side analysts typically fill out the questionnaires. To the best of our knowledge, this dataset has not yet been used for this purpose.

Table 3.1: Survey data set description

Surveying institution	FX Weekly	
Exchange rates	\$/€, \$/£, ¥/€, ¥/\$	
Frequency	weekly, unbalanced	
Forecast horizons	1, 3 and 12 months	
no. Participants	61	
Background respondents	Financial institutions	
Average response rate	51.16 %	
Sample period	Jan 03 – Feb 08	
	respondents	**periods**
Minimum no. of	9	3
Maximum no. of	41	217
Median no. of	37	142

[10] FX Week is an industry newsletter for foreign exchange and money market professionals working within commercial banks, investment banks, central banks, brokerages, institutional investors, multinational corporations and vendor companies serving the banks and financial institutions.

[11] Although the survey data are time-stamped on Monday, we cannot be sure at which day expectations were formed exactly. To control for possible information asymmetries, we ran all analyses using exogenous data from the same Monday as well as the Friday before that. Results are highly similar and available upon request.

A typical problem that may arise with survey forecasts is that respondents do not reveal their true expectations, perhaps because of private information that they do not want to reveal. However, because the names of the respondents of this survey have been made public, it is not likely that this problem will arise[12]. After all, there is also a reputational aspect to revealing your forecast, and, therefore, we believe that the investors have an incentive to reveal their true expectations[13],[14]. The Bank of International Settlement Triennial Survey (2010) states that the vast majority of foreign exchange activity occurs between large financial institutions such as the ones in our sample. Hence, our sample of institutions can be regarded as representative for the foreign exchange market.

As we can see in Table 3.1, the data were sampled at a weekly frequency for the one-, three- and twelve-month forecast horizon. A total number of 61 investors from large renowned banks and investment companies participated in the survey. From January 2003 to February 2008, forecasts were made for the spot rate of the U.S. dollar against the Japanese yen (USDJPY), the pound sterling (GBPUSD) and the euro (EURUSD), and for the euro against the Japanese yen (EURJPY). The data analysis will mainly be conducted in a panel structure. The panel is unbalanced as there are some one- or two-week gaps, and some panelists left or entered the survey.

Spot exchange rates and interbank lending rates were gathered from Datastream, as were the PPP exchange rates for the fundamental forecasting rules[15]. The OECD PPP rate is used as fundamental PPP value for the exchange rates, as this is a widely used and highly valued measure[16]. A drawback of the OECD rate is that its frequency (annual) does not correspond to the frequency of our survey data (weekly) and therefore contains less variation. However, a rather stable fundamental value is theoretically viable.

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[12]See, for example: http://www.e-forex.net/news/e-FX+News/100625/TMS+Brokers+tops+forecast+rankings and https://research.standardchartered.com/about/foreignexchange/Pages/default.aspx?teamId=10.

[13] In this respect, the terms expectations and forecasts will be used interchangeably in this paper, as we assume that the investors' forecasts are unbiased representations of their expectations. Jongen et al. (2011) also confirm the value of survey forecasts for this purpose.

[14] Forecasts are generally given by FX analysts or strategists working at the banks, we can therefore not say with certainty that the banks will also commit their capital accordingly. However, forecasts given by people on the sell-side of a bank influence investment decisions on the buy-side, which makes them a useful proxy for market expectations.

[15] Spot exchange rates: WM Reuters. Interbank rates: British Bankers' Association. PPP rates: OECD.

[16] For instance, Deutsche Bank offers a PPP ETF that is based on the PPP measure of the OECD; see DBIQ.com.

Table 3.2: Descriptive statistics of log expected and log realized returns

	eurjpy 1m		eurjpy 3m		eurjpy 12m		eurusd 1m		eurusd 3m		eurusd 12m	
	exp	real	exp	real	exp	real	exp	real	exp	real	exp	real
Mean	-0.0044	0.0044	-0.0094	0.0108	-0.033	0.0156	0.0015	0.0069	0.0074	0.0163	0.0176	0.045
Median	-0.0067	0.0085	-0.0136	0.0177	-0.0418	0.029	0.0008	0.0068	0.0057	0.0174	0.0219	0.0612
Maximum	0.0431	0.0626	0.042	0.0924	0.0697	0.1445	0.033	0.0746	0.0499	0.1031	0.0864	0.1919
Minimum	-0.0358	-0.0823	-0.0504	-0.0839	-0.0792	-0.3249	-0.0409	-0.0558	-0.0395	-0.0889	-0.0498	-0.1528
High-Low	0.0789	0.1449	0.0924	0.1762	0.1489	0.4694	0.0739	0.1304	0.0894	0.1919	0.1362	0.3447
Std. Dev.	0.0119	0.025	0.0167	0.0335	0.0341	0.0963	0.0122	0.0269	0.0162	0.0413	0.0308	0.0824
Skewness	0.9146	-0.7012	0.7592	-0.5821	1.0613	-2.0235	0.0334	0.1386	0.2131	-0.2387	-0.2007	-0.731
Kurtosis	4.7088	3.9569	3.1865	3.0642	3.3274	7.122	3.0602	2.647	2.2951	2.8096	2.3113	2.7136
Jarque-Bera	56.3947	25.9392	21.0636	12.2346	41.517	300.3187	0.0727	1.8126	6.1066	2.3776	5.7192	19.9765
Probability	0	0	0	0.0022	0	0	0.9643	0.404	0.0472	0.3046	0.0573	0
	gbpusd 1m		**gbpusd 3m**		**gbpusd 12m**		**usdjpy 1m**		**usdjpy 3m**		**usdjpy 12m**	
	exp	real	exp	real	exp	real	exp	real	exp	real	exp	real
Mean	-0.0006	0.004	0.0004	0.0093	-0.0048	0.0112	-0.0056	-0.0024	-0.017	-0.0056	-0.0519	-0.0294
Median	-0.0008	0.0057	0	0.011	-0.0053	0.0357	-0.0064	-0.0016	-0.0176	-0.0016	-0.0576	-0.0244
Maximum	0.0265	0.0666	0.0434	0.1107	0.0537	0.1675	0.038	0.0675	0.0369	0.1007	0.0403	0.1648
Minimum	-0.0319	-0.0532	-0.035	-0.0918	-0.056	-0.3383	-0.0478	-0.0864	-0.0724	-0.1224	-0.1215	-0.2289
High-Low	0.0584	0.1199	0.0784	0.2025	0.1096	0.5058	0.0858	0.1539	0.1093	0.2231	0.1617	0.3937
Std. Dev.	0.0108	0.0251	0.0144	0.0377	0.0233	0.1112	0.0139	0.0269	0.0201	0.0402	0.0362	0.0841
Skewness	-0.1844	0.025	0.1268	0.0742	0.0753	-1.4663	0.2128	-0.4137	0.1559	-0.2558	0.4912	0.0343
Kurtosis	2.9423	2.6028	2.928	3.0969	2.3657	5.0012	3.3434	3.1258	2.7718	2.7777	2.5052	2.1885
Jarque-Bera	1.2536	1.442	0.6255	0.2826	3.8256	113.44	2.6915	6.3032	1.3436	2.8008	10.8891	5.9697
Probability	0.5343	0.4863	0.7314	0.8682	0.1477	0	0.2603	0.0428	0.5108	0.2465	0.0043	0.0505

Table 3.2 shows the descriptive statistics for the expected returns and corresponding realized returns. From the negative period mean expectations of the one-, three- and twelve-month future EURJPY, GBPUSD and USDJPY exchange rates we can see that investors expected an overall depreciation of the yen against the euro and the dollar as well as a depreciation of the dollar against the pound. The standard deviations of the forecasts are very high compared to the means, suggesting that the mean expectations are rather volatile across individuals and over time. Standard deviations increase as the forecast horizon increases. Another interesting feature is that the high-low statistic, which shows the difference between the maximum and the minimum observations, increases with the forecast horizon.

It is interesting to compare these statistics to the descriptive statistics of the realized returns, where there is a positive mean for the first three currencies and a negative mean for the USDJPY. This means that for both the EURJPY and the GBPUSD exchange rates, investors were not able to predict the correct sign of the mean returns over time. Similar to the standard deviation of the forecasts, the standard deviation of the realized returns is high, which shows the high volatility of the foreign exchange markets. The high kurtosis shows that the distribution of the expectations is fat-tailed, which is in line with realized returns.

The following section will describe the methodology used to evaluate which forecasting strategies are used.

3.3 Methodology

To investigate investors' forecasting strategies, we assume that the investors have equal access to information, but they interpret it differently by attaching different weights to different sources of information when forming expectations. A result of the overconfidence bias (Fischhoff et al., 1977) is that agents try to detect patterns in the exchange rate movements to predict future exchange rates while the foreign exchange market actually shows a random walk. Bloomfield and Hales (2002) indicate this in their two experiments with MBA participants. These participants used past price changes as an indicator for future reversals even though they were told that the sequences they were dealing with were random walks.

In contrast to traditional finance theory, several studies in the behavioral finance domain assume that agents use different models to process information into expectations. As noted by

Hong and Stein (1999), a necessary condition for alternatives to the rational expectations setup is that there is empirical evidence supporting the alternative to bound the imagination of the researcher. The models that are widely used in the foreign exchange literature are momentum trading and PPP trading. Next to these two models, an additional model is tested that is based on the interest differential between the countries. A study from Pojarliev and Levich (2008) reveals that these trading strategies explain a substantial portion of the variability in foreign exchange funds. The choice for these models is further supported by the ETF prospects of Deutsche Bank and Barclays Capital. Deutsche Bank shows in its prospectus that the bank uses a combination of a carry, momentum and valuation strategy, in which the valuation strategy is based on the OECD's purchasing power parity rate. Barclays capital uses a combination of carry and value strategy (also based on OECD PPP rates). Allen and Taylor (1992) indicate that PPP is the fundamental model traders tend to apply.

3.3.1 Momentum traders

The first type of investor that we distinguish is the momentum trader, also referred to as trend chaser or (positive) feedback trader. According to Allen and Taylor (1990, 1992), approximately 90% of investors in the foreign exchange market use some form of technical analysis to predict future changes of exchange rates. Andreassen and Kraus (1990) indicate that investors are likely to sell if prices decline and to buy if prices increase, which is a form of trading on momentum. De Bondt (1993) confirms these findings with survey results that suggest people are optimistic in bull markets and pessimistic in bear markets.

Momentum trading is a deviation from rationality that can partly be assigned to representativeness bias. Representativeness (Tversky and Kahneman, 1974) can occur when people have to determine the probability that a series of returns generates some price or return. Rather than looking at the base rates and the overall distribution of returns, they look for similarities and think that the past returns are representative of the forecasting period.

The most basic form of a momentum rule is a simple AR(1) rule:

$$s_{t+k,i}^{e} - s_t = \alpha + \beta(s_t - s_{t-k}) + \varepsilon_{t,i} \tag{3.1}$$

where *k* denotes the forecast horizon. In case $\beta>0$, agents using this strategy expect price trends to continue. Agents are then said to be destabilizing as they drive the exchange rate in one direction. This is also referred to as bandwagon expectations. If $\beta<0$, traders show opposite behavior, which means that they expect past price movements to revert. This is also known as contrarian strategy.

Several studies (Frankel and Froot, 1987a,c, 1990; Cavaglia et al., 1993; Ito, 1990) show that bandwagon effects especially occur in the short run (depending on the study, up to 1 to 3 weeks) but disappear or turn into contrarian effects for longer horizons. This is in line with the findings of Cutler et al. (1991) of short-term positive auto-correlation and long-term negative auto-correlation of returns. Because the expectation formation process is the same for bandwagon and contrarian strategies, except for the change in sign of the explanatory coefficient, it is difficult to distinguish these effects. It is possible that some investors show extrapolative behavior and others act in a stabilizing way. When these even out on the macro level, making the extrapolation coefficient insignificant, it might not have an effect on the price; however, we cannot observe the true heterogeneity of the agents. In times of crisis or other financial turmoil, the bandwagon type may begin to dominate, causing severe destabilizations of the market. For these situations, it is useful to make a distinction between bandwagon and contrarian expectations. To the best of our knowledge, this distinction has not been made before in estimating these kinds of models. To determine whether the sign we find in Equation (3.1) represents a single type of investor or is a composition of a contrarian and bandwagon models, we estimate the following equation:

$$s_{t+k,i}^{e} - s_t = \alpha + \beta_1 D^b (s_t - s_{t-k}) + \beta_2 (1 - D^b)(s_t - s_{t-k}) + \varepsilon_{t,i} \qquad (3.2)$$

where D^b is a dummy accounting for positive extrapolation (bandwagon effects), which takes the value of 1 if the past price movement and the individual expectation are of the same sign and 0 otherwise. This introduces a form of dynamics in the expectation formation as we allow the investors to switch between bandwagon and contrarian behavior.

3.3.2 PPP traders

PPP traders use the purchasing power parity value of the exchange rate as an anchor in forming their expectations. They expect the exchange rate to revert back to this value. This means that they expect prices of overvalued assets to decrease and prices of undervalued assets to increase until the price of the asset reflects its PPP value. In the behavioral finance literature, this behavior is often referred to as 'regressive' or 'mean reverting,' as it assumes reversion to some kind of mean. Note that trading based on the fundamental value of the exchange rate (in this case, the PPP rate) would be rational if there were no other types of investors in the market. However, as past studies have found that there are different types of actors, it would be boundedly rational to fully adhere to this strategy without acknowledging the deviations from market efficiency.

Obtaining the PPP value of an exchange rate is not straightforward. Economic literature is unclear about the true PPP value. Several versions of the model have been suggested in which the discussion is usually about the use of different price indices (Xu, 2003). As this is an empirical survey study, we are not concerned about whether we are using the correct PPP estimate or whether the PPP rate is the actual fundamental value; rather, we care only if investors assume this to be true and therefore use it in their expectation formation process. Although this does not particularly make it more straightforward, we can make some assumptions.

Investors in the foreign exchange market need information to form expectations and to make investment decisions. This information is costly, especially with respect to information that is not directly observable, such as the PPP value of the exchange rate. Before gathering this information, investors are likely to make some sort of cost-benefit analysis: when do the costs of obtaining this value exceed the benefits? Based on this behavior, we selected the OECD PPP value of exchange rates as an approximation of the true PPP value, as it does not require complicated analyses, models and calculations, and it is available against low costs. Furthermore, as indicated above, it is used by Deutsche Bank and Barclays as a benchmark for their value ETFs.

Figure 3.1 displays the OECD PPP rates and the nominal exchange rates used in this study. Figure 1 shows that the exchange rate is heavily mispriced the majority of the time. The

USDJPY seems to be consistently lower than the PPP rate, whereas the GBPUSD and the EURUSD show the opposite trend beginning at the end of 2003. This indicates that the U.S. dollar was underpriced against the euro, the yen and the pound for over four years. Interestingly, the yen rates appear to move in the opposite direction from the fundamental rate. Whereas the PPP rate is decreasing for both exchange rates, the spot rates are generally increasing. We do not see this effect for the other two currencies. Both the perverse movements and the constant mispricing may have effects on PPP trading strategies.

PPP traders base their expectations on the deviation between the price and the PPP rate of an asset. They perceive such a situation as a mispricing, that is, an undervaluation or overvaluation of the currency.

$$s^e_{t+k,i} - s_t = \alpha + \gamma(\bar{s}_t - s_t) + \varepsilon_{t,i} \qquad (3.3)$$

where $\bar{s}$ is the PPP rate. The equation shows that the price movement expected by these traders is caused by the deviation of the price from the PPP value. For a positive γ, they are stabilizing, that is, they expect the exchange rate to revert to its PPP-based value, whereas a negative value of γ implies destabilizing behavior.

The second type of PPP trading behavior we test incorporates a non-linear response to the deviation from the PPP value (Taylor et al., 2001). The idea behind this is that a mean reverting expectation is more likely and probably stronger if the exchange rate is far from its PPP value. In such a situation, investors believe that chances are high the exchange rate will revert to this value. On the other hand, if the exchange rate is close to its PPP value, the risk of trend extrapolation is too big and the transaction costs are too high to benefit from fundamental analysis. This effect is captured by taking the deviation to the power of three:

$$s^e_{t+k,i} - s_t = \alpha + \gamma(\bar{s}_t - s_t)^3 + \varepsilon_{t,i} \qquad (3.4)$$

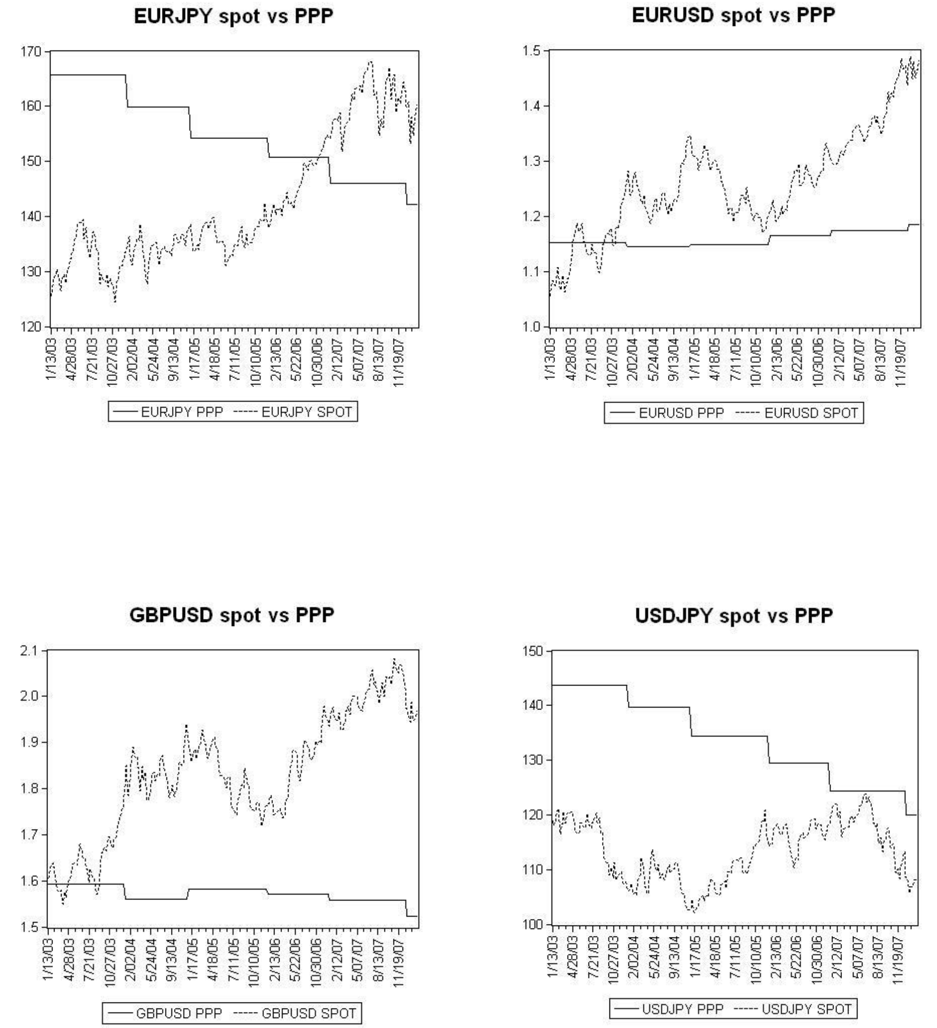

Figure 3.1 Nominal and PPP rates (natural logarithms).

3.3.3 Interest differential traders

Many violations of the UIP relationship have been recorded, resulting in a branch of literature that focuses on the 'interest parity puzzle' (see Sarno (2005) for an overview). It is quite plausible that the UIP puzzle exists because of the presence of non-rational expectations. Then, when these deviations appear to be persistent, they get picked up by investors who try to use the deviation to make a profitable trade. This may result in carry trade, of which many cases have been observed in the past decades. Carry trade occurs under the exact opposite assumptions from uncovered interest parity in the sense that carry traders exploit the interest differential by borrowing in the low-interest country and lending in the high-interest country.

$$s^e_{t+k,i}\text{-}s_t = \alpha + \vartheta(i_t\text{-}i^*_t) + \varepsilon_{t,i} \qquad (3.5)$$

The sign of ϑ indicates whether investors apply carry trade or uncovered interest parity in their expectations. A positive value of ϑ reveals trading based on uncovered interest parity[17], whereas a negative value reveals that there are carry traders in the market.

As was the case for momentum traders, we have the problem of two different strategies that both use the same information but do so in an exact opposite manner. In this case, it would be interesting to determine if there is actually only one type of trader that uses the interest differential or if there are both carry traders and UIP traders. We attempt to reveal this in a similar way to what we did for momentum traders, by estimating the equation:

$$s^e_{t+k,i}\text{-}s_t = \alpha + \vartheta_1 D^{uip}(i_t\text{-}i^*_t) + \vartheta_2(1\text{-}D^{uip})(i_t\text{-}i^*_t) + \varepsilon_{t,i} \qquad (3.6)$$

where $\vartheta_1 D^{uip}(i_t - i^*_t)$ $(\vartheta_2(1 - D^{uip})(i_t - i^*_t))$ reveals uncovered interest parity (carry trade) expectations and is the interest differential multiplied by a dummy with the value of one (zero) if the individual's forecast and the interest differential are of the same sign and a value of zero (one) otherwise.

[17] Formally, only a value of ϑ of 1 corresponds to uncovered interest parity, but because of limits to arbitrage and the fact that the coefficient is an 'average' over all respondents, we say that a positive coefficient indicates sentiment towards UIP and a negative coefficient is a clear sign of carry trade.

3.3.4 Heterogeneity: combined model

If we find the individual models to be significant, it becomes interesting to merge them into one model to exclude the possibility of omitted variable bias by testing whether the coefficients are still significant. For the combined model, we begin with the basic Equations (3.1), (3.3) and (3.5) for the momentum, PPP and interest differential trade models, respectively.

$$s_{t+k,i}^{e} - s_t = \alpha + \beta(s_t - s_{t-k}) + \gamma(\bar{s}_t - s_t) + \vartheta(i_t - i_t^{*}) + \varepsilon_{t,i} \qquad (3.7)$$

As for the separate strategy models, this model is tested on the whole panel of investors over the entire survey sample. A valuable feature of testing this combined model on the different time horizons is that it enables us to see whether the strategies change in significance and dominance for increasing forecasting horizons. Bandwagon effects are usually only seen on short horizons[18], whereas contrarian behavior is observed for medium and long horizons, so we would expect β to change sign for three- and twelve-month horizons. Additionally, exchange rates generally need a long time to revert to their PPP value. Rogoff (1996) indicates that the half-life of most exchange rates is three to five years. We can therefore expect that this strategy only becomes significant for the longer horizons. The extent of the effect of horizon on the interest differential parameter is not straightforward. Nevertheless, we can characterize uncovered interest parity as a more fundamental strategy (i.e., more appropriate for longer horizons) and carry trade as a speculative strategy (for short horizons). With this characterization, we expect to see a negative parameter for the one-month horizon, which turns into a positive parameter for the twelve-month horizon.

The sophisticated model includes adjustments to the different strategies. This means it allows for dynamics within the group of momentum traders and interest differential traders. The choice for the linear PPP model is motivated by ease of interpretation of the coefficient and the added complexity of the non-linear model[19].

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[18] Short horizons in this context are usually defined as 1-3 week horizons, so it is unclear whether the 1 month horizon qualifies as short or medium horizon.

[19] We also estimated the sophisticated model with the nonlinear response to the fundamental deviations, and this generated similar results.

$$s^e_{t+k,i}\text{-}s_t = \alpha + \beta_1 D^b \left(s_t\text{-}s_{t\text{-}k}\right) + \beta_2\left(1\text{-}D^b\right)\left(s_t\text{-}s_{t\text{-}k}\right) + \gamma\left(\bar{s}_t\text{-}s_t\right)$$
$$+\vartheta_1 D^{uip}\left(i_t\text{-}i^*_t\right) + \vartheta_2\left(1\text{-}D^{uip}\right)\left(i_t\text{-}i^*_t\right) + \varepsilon_{t,I} \qquad (3.8)$$

3.3.5 Time-varying rules

In the previous sections, we have assumed that agents put constant weights on the forecasting rules that they use. However, both theory and empirical evidence (Barberis and Shleifer, 2003; Prat and Uctum, 2007; Bloomfield and Hales, 2002; Branch, 2004) suggest that agents change the weights assigned to a certain strategy. This is often referred to as 'switching' between rules. In this section, we will investigate whether the survey data confirms the assumption of evolving weights to forecasting rules. In doing so, we will follow the approach used in the heterogeneous agent literature and introduced by Brock and Hommes (1997, 1998) by using a switching rule that is based on the forecasting accuracy of a certain strategy. To do this, we use mean expectations of agents. De Jong et al. (2010) apply a heterogeneous agent model to the foreign exchange rate. Estimation results for the EMS period reveal significant heterogeneity and switching between rules.

To capture agents' switching between forecasting rules, we update Equation (3.7) with a weighting function:

$$s^e_{t+k} - s_t = \alpha + W^c_t \beta(s_t - s_{t-k}) + W^f_t \gamma(\bar{s}_t - s_t) + W^i_t \vartheta(i_t - i^*_t) + \varepsilon_t \qquad (3.9)$$

where W^c_t, W^f_t and W^i_t are the weights assigned to the momentum, PPP and interest differential rules, respectively. How much weight agents put on a certain strategy depends on the forecasting accuracy of this strategy. The weights are, therefore, computed as:

$$W^s_t = \frac{\exp(\rho\pi^s_t)}{\sum_{s=f,c,i}\exp(\rho\pi^s_t)} \qquad (3.10)$$

which is based on the model of Brock and Hommes (1997, 1998). The weight assigned to strategy *s* is a function of the performance of strategy *s* on time *t* (π^s_t) divided by the sum of all performances. The performance of a strategy is given by the previous period's squared forecast error for that strategy[20], given by

$$\pi_t^c = ((\beta(s_{t-k} - s_{t-2k})) - (s_t - s_{t-k}))^2$$
$$\pi_t^f = ((\gamma(\overline{s_{t-k}} - s_{t-k})) - (s_t - s_{t-k}))^2$$
$$\pi_t^i = ((\vartheta(i_{t-k} - i_{t-k}^*)) - (s_t - s_{t-k}))^2 \qquad (3.11)$$

The rationale behind these equations is that investors compare the real past change of the exchange rate with the change that was predicted by each of the models. The model with the smallest forecast error, that is, the model that had the best prediction in the previous period, should receive the highest weight in the coming period. Therefore, we expect the switching parameter ϱ to be negative. If this parameter is positive, agents switch to the rule that performed worst in the previous period.

The switching parameter is often referred to in the literature as the intensity of choice, and it captures the delay in agent response to changes in performance. It is negatively related to the status quo bias described by Samuelson and Zeckhauser (1988), implying that people do not immediately change their behavior if they observe that this is desirable unless the reasons are appealing enough to do so. A high (absolute) ϱ implies that the status quo bias is low, whereas the opposite occurs for a low (absolute) ϱ.

In Section 4, we will present and evaluate the results from estimating the above equations. All regressions in Sections 4.1 to 4.4 are estimated using ordinary least squares on panel data with fixed effects[21], which captures some level of individual heterogeneity by allowing for individual specific intercepts. We account for the autocorrelation in the residuals, induced by the overlapping observations problem[22], with a White correction to the standard errors. In Section 4.5, mean expectations are used in combination with a nonlinear least squares estimation, in which a Newey-West adjustment is used to account for autocorrelation

[20] Experiments with alternative functional forms, such as absolute forecast errors, yield similar results.

[21] A likelihood ratio test showed that the null hypothesis of redundant fixed effects was rejected. A Hausman test revealed the redundancy of random effects. Therefore, a model with fixed effects was appropriate.

[22] As the forecasts are weekly, and the horizons are one month or longer, the next forecast is made before the first forecast has expired. This would almost certainly lead to autocorrelation in the empirical model residuals (see MacDonald, 2000).

in residuals. Accounting for serial correlation is necessary because of the overlapping character of the forecasts.

3.4 Results

3.4.1 Momentum traders

Section 4.1 describes the results from estimating the momentum models on the investor expectations. In this section, all equations are estimated on the full panel. Table 3.3 presents the results from estimating the basic momentum trading model from Equation (3.1).

Regarding the basic setup, on the left side of the Table, the negative coefficients for all currencies[23] and all forecast horizons indicate that momentum traders on the foreign exchange market are contrarian rather than extrapolative, especially for the Japanese yen against the euro and the U.S. dollar, where it is clear that momentum traders are mainly active on short horizons as the magnitude and significance of the coefficient decreases for an increasing forecast horizon. This is in line with results of earlier studies, which suggest that negative feedback trading mainly occurs at relatively long forecast horizons. The opposite effect is noticeable for the EURUSD, where the strategy becomes significant for the twelve-month horizon only. Interestingly, the fit differs considerably between the currencies. This indicates that apart from the significant presence for all currencies, momentum traders are more active in the EURJPY and EURUSD markets than in the GBPUSD market. The model fit generally increases with the forecast horizon.

There are two possible reasons for the small and sometimes insignificant coefficients of the basic momentum rule. Either investors that trade in these markets do not use (this form of) momentum in forming forecasts, or the group of contrarians and the group of positive extrapolators are of similar size, causing the effects to even out.

By testing Equation (3.2), we can see which of these explanations is most plausible. The results are displayed on the right hand side of Table 3.3. It is worth noting that there are, indeed, two types of trend extrapolators active in this market with opposing beliefs about how to extrapolate trends. In general, the contrarian effect dominates given the significance and

[23] Except for the one-month GBPUSD, but this coefficient is not significant.

effect size, which is why we see negative coefficients for the basic model. An interesting result is observed for the EURJPY as it reveals opposite extrapolation effects. Rather than short-term positive feedback trading and long-term negative feedback trading, the traders on these markets expect the exact opposite to happen. Over the short term, there is a dominance of contrarian expectations, whereas over the long term, the bandwagon effect dominates. This unconventional way of expectation formation is not observed for the other two exchange rates. This might have to do with the fact that the yen moves opposite to its fundamental value, overall (see Figure 3.1). Furthermore, we can see that the effect of momentum traders in the market for GBPUSD is limited, as the coefficients are small. However, when split into a bandwagon and a contrarian effect, they turn significant. As the coefficients of these strategies are very similar in absolute terms, it is plausible that their effects even out on an aggregated level, which explains the insignificant coefficients in Equation (3.1). The same argument applies to the one-month EURUSD expectations.

3.4.2 PPP traders

As we can see in Table 3.4, where the results from estimating Equation (3.1) are displayed, PPP traders appear to be mainly active in the EURUSD and the GBPUSD markets. This means that, again, the traders show deviating behavior with respect to the Japanese yen FOREX market, as the PPP strategy is not used much for these currencies. The EURUSD reveals the expected results over different horizons, namely, a growing magnitude of the coefficients for longer forecast horizons. All significant results show the correct sign, thus indicating that PPP traders are stabilizing by expecting the exchange rate to revert to its PPP value.

If we allow for non-linearity in the PPP rule, on the right side of the table, the results become significant for three of the four exchange rates. These results provide some evidence for the assumption that PPP traders become increasingly active in the market when the exchange rate moves further away from its fundamental value. Within this model, we can clearly see that PPP strategies are mainly used for longer horizons, as the fit of the model increases from one to twelve months. Again, we cannot find significant coefficients for the USDJPY.

Table 3.3: Results momentum

		Basic					Dynamic						
		constant		**momentum**		**adj R^2**	**constant**		**bandwagon**		**contrarian**		**adj R^2**
EURJPY	**1m**	-0.0039	***	-0.3888	***	0.2418	-0.0029	***	0.4247	***	-0.6541	***	0.5205
		-85.887		-19.4223			-67.478		21.846		-40.324		
	3m	-0.0096	***	-0.1885	***	0.117	-0.0062	***	0.5935	***	-0.6879	***	0.4521
		-27.178		-5.8352			-29.459		20.196		-28.719		
	12m	-0.0375	***	-0.0958		0.228	-0.0333	***	0.6738	***	-0.381	***	0.5083
		-10.755		-1.492			-13.951		9.8658		-8.1092		
EURUSD	**1m**	0.0048	*	-0.0061		0.0928	0.0019		0.0254	***	-0.0296	***	0.542
		1.8671		-1.1647			1.2445		7.1316		-10.356		
	3m	0.0169	***	-0.0205	*	0.1782	0.0091	***	0.0315	***	-0.0571	***	0.588
		2.9086		-1.6888			2.9319		4.5281		-9.2028		
	12m	0.0636	***	-0.1173	***	0.3972	0.037	***	0.0206		-0.1503	***	0.6969
		4.6049		-3.6495			4.1		0.9095		-7.6269		
GBPUSD	**1m**	-0.006		0.0043		0.0614	-0.0045		0.0143	***	-0.0081	***	0.5718
		-0.8998		0.8028			-1.1588		4.4133		-2.6969		
	3m	0.0018		-0.002		0.061	-0.0024		0.0127	***	-0.0098	***	0.5716
		0.2911		-0.3931			-0.6325		3.9192		-3.3177		
	12m	0.0055		-0.0052		0.0616	-0.0006		0.0117	***	-0.0116	***	0.5719
		0.7788		-0.8697			-0.1328		2.8719		-3.0745		
USDJPY	**1m**	-0.0074	***	-0.4353	***	0.3539	-0.0054	***	0.293	***	-0.6571	***	0.5716
		-142.76		-22.174			-92.666		13.456		-34.66		
	3m	-0.0196	***	-0.3329	***	0.2661	-0.0138	***	0.2892	***	-0.6948	***	0.4706
		-314.4		-11.541			-40.879		6.8926		-23.982		
	12m	-0.0592	***	-0.2637	***	0.3633	-0.0441	***	0.2955	***	-0.6605	***	0.5128
		-193.88		-5.8458			-35.304		4.6647		-19.474		

Coefficients and t-statistics (shaded) from estimating Equation 3.1 and Equation 3,2. Significance is listed as ***, **, * for significance on 1%, 5% or 10% level respectively.

Table 3.4: Results PPP

		Basic					Non-linear				
		c		**PPP**		**adj R²**	**c**		**PPP^3**		**adj R²**
EURJPY	**1m**	-0.0048	***	3E-04		0.0402	-0.006	***	0.3622	**	0.0441
		-14.74		0.057			-17.02		2.298		
	3m	-0.0117	***	0.002		0.0873	-0.014	***	0.8775	**	0.0967
		-12.499		0.092			-14.85		1.9936		
	12m	-0.0474	***	0.084	*	0.2463	-0.05	***	3.6655	***	0.2747
		-18.703		1.859			-19.77		2.9735		
EURUSD	**1m**	0.0057	***	0.04	***	0.1038	0.0033	***	0.7569	***	0.1024
		5.0844		3.483			8.2771		3.804		
	3m	0.0142	***	0.073	***	0.1894	0.0102	***	1.5321	***	0.1908
		5.9347		2.986			10.184		3.0937		
	12m	0.0487	***	0.362	***	0.4582	0.0276	***	7.1707	***	0.4545
		8.3863		6.111			12.909		6.7418		
GBPUSD	**1m**	0.0029	*	0.02	**	0.0649	0.0005		0.1551		0.0631
		1.7354		2.125			0.6986		1.6153		
	3m	0.0093	***	0.056	***	0.1377	0.0031	*	0.4928	**	0.1346
		2.7185		2.86			1.841		2.124		
	12m	0.0375	***	0.266	***	0.4264	0.0108	***	2.6544	***	0.4239
		5.2212		6.439			3.5318		6.4034		
USDJPY	**1m**	-0.0059	***	-0.002		0.0901	-0.007	***	0.1153		0.0913
		-5.1966		-0.281			-12.89		1.443		
	3m	-0.0154	***	-0.023		0.1539	-0.019	***	-0.047		0.1515
		-5.6248		-1.287			-14.73		-0.2541		
	12m	-0.0524	***	-0.032		0.3017	-0.057	***	-0.0435		0.3003
		-7.9246		-0.753			-18.49		-0.0962		

Coefficients and t-statistics (shaded) from estimating Equation 3.3 and Equation 3.4. Significance is listed as ***, **, * for significance on 1%, 5% or 10% level respectively.

Table 3.5: Results interest differential

		Basic					UIP & Carry						
		c		**uipcarry**		**adj R²**	**c**		**Carry**		**UIP**		**adj R²**
EURJPY	**1m**	-0.0102	***	-0.208	**	0.0434	-0.0072	***	-0.8032	***	0.3512	***	0.5617
		-3.7829		-2.0125			-5.6279		-16.333		6.618		
	3m	-0.0219	***	-0.3847		0.092	-0.0125	***	-1.1943	***	0.5988	***	0.5812
		-2.8132		-1.313			-3.7028		-8.6116		4.6834		
	12m	-0.0112		1.1528		0.2336	-0.0157		-1.5264	***	1.6536	***	0.5741
		-0.4998		1.3964			-1.2427		-3.353		3.4869		
EURUSD	**1m**	0.0018	***	-0.0019		0.0914	0.0008	***	-0.8815	***	0.9122	***	0.4592
		5.0955		-0.0434			2.5213		-17.705		15.748		
	3m	0.0062	***	0.1038		0.1737	0.0033	***	-1.5418	***	1.3869	***	0.515
		9.4814		1.284			5.737		-17.716		16.414		
	12m	0.0003		1.2227	***	0.3852	0.0029	**	-2.7433	***	2.8396	***	0.6315
		1.3801		4.3455			2.2195		-9.2416		16.532		
GBPUSD	**1m**	-0.0014	*	-0.0562		0.062	-0.0017	***	-0.7328	***	0.602	***	0.431
		-1.8457		-0.9702			-3.0942		-18.802		9.9389		
	3m	-0.0003		0.0131		0.125	-0.001		-1.0661	***	1.0732	***	0.4931
		-0.215		0.111			-0.8987		-15.54		8.0704		
	12m	-0.0034		0.4512	*	0.3372	-0.0022		-1.3434	***	1.9356	***	0.5623
		-1.0739		1.7226			-0.918		-7.0672		7.4367		
USDJPY	**1m**	0.0064	***	-0.0039		0.0901	-0.0055	***	-0.5098	***	0.3489	***	0.5343
		-4.0887		-0.0852			-5.3215		-14.541		10.491		
	3m	-0.0165	***	0.0691		0.1521	-0.0147	***	-0.8666	***	0.5105	***	0.5443
		-4.3478		0.6307			-6.4663		-10.701		7.453		
	12m	-0.0145		1.2119	***	0.3421	-0.0301	***	-1.4859	***	1.2319	***	0.5932
		-1.3108		3.8914			-3.8769		-5.784		5.5814		

Coefficients and t-statistics (shaded) from estimating Equation 3.5 and Equation 3.6. Significance is listed as ***, **, * for significance on 1%, 5% or 10% level respectively.

The non-linear model performs worse in terms of model fit than the basic model in half of the cases, which makes the additional value of this model questionable.

3.4.3 Interest differential traders

The results of regressing Equation (3.5) can be found on the left side of Table 3.5. The evolution of the coefficients over the forecast horizons suggests that the interest differential is indeed used for carry trade for shorter horizons and that it follows the theory of uncovered interest parity for horizons of twelve months. However, none of the currencies have both significant short- and long-term effects at the same time. From the fit of the model, it seems that the information from the interest differential is mainly used for long forecast horizons and that we can find some evidence for UIP in expectations.

Again, as we have seen for the momentum rule, the insignificant results might imply that the interest differential is not popular to use in forming expectations or that there are both carry traders and UIP traders in the market who cancel out each other's effects. Support for both strategies can be found on the right side of Table 3.5, which represents the results from estimating Equation (3.6). For all exchange rates and forecast horizons, the effects are significant at a 1% level. Therefore, it can be stated that both strategies are being used in the foreign exchange market, but their effect is only marginal, as they even out on an aggregated level. The difference between the carry and UIP coefficients suggests that there is a shift from carry towards UIP expectations as the forecast horizon increases. The fit of the model increases over time, indicating that the information from the interest differential is used particularly for longer horizons[24].

3.4.4 Heterogeneity: combined model

By estimating Equation (3.7) on the full panel, we attempt to discover whether institutional investors use the three simple rules of thumb. Combining all the strategies in one

[24] Note that a carry trade strategy is more difficult to detect, as this strategy is already profitable if the expected change in exchange rate is lower than the profit made on the interest differential.

model reduces the risk of omitted variable bias and controls for potential correlations between models[25]. Results are displayed in Table 3.6.

Table 3.6: Results heterogeneity (basic model)

		c		momentum		PPP		uip/carry		adj R^2
EURJPY	**1m**	-0.0229	***	-0.3792	***	0.0271	***	-0.6667	***	0.247
		-4.8818		-19.576		2.861		-4.0962		
	3m	-0.0888	***	-0.1598	***	0.1322	***	-2.6933	***	0.1472
		-7.775		-5.273		5.7858		-6.8163		
	12m	-0.151	***	-0.027		0.2458	***	-3.5286	***	0.2587
		-5.8486		-0.4129		3.5912		-4.5714		
EURUSD	**1m**	-0.0634	***	0.2534	***	0.5767	***	-0.1721	***	0.2135
		-12.67		15.04		15.938		-3.5523		
	3m	0.0183	***	0.1154	***	0.2986	***	-0.0563		0.2086
		-2.473		5.0013		6.6323		-0.6539		
	12m	0.0379	***	0.006		0.3391	***	0.7167	***	0.4728
		3.0587		0.1766		4.6246		2.6423		
GBPUSD	**1m**	-0.2618	***	0.2792	***	0.5025	***	-0.0892		0.2
		-13.587		13.571		13.644		-1.5873		
	3m	-0.0729	***	0.087	***	0.2018	***	0.0228		0.1475
		-2.8699		3.2591		4.2384		0.1985		
	12m	0.0065		0.0486		0.3321	***	0.2226		0.4351
		-0.1739		1.2888		5.3225		0.9751		
USDJPY	**1m**	0.0092	**	-0.4506	***	-0.0515	***	0.255	***	0.3639
		2.2127		-22.935		-4.3519		3.3461		
	3m	0.0088		-0.344	***	-0.0958	***	0.3957	***	0.2835
		1.0641		-12.194		-3.8086		2.679		
	12m	0.0149		-0.2914	***	-0.254	***	0.9923	**	0.4151
		0.7153		-5.4703		-5.141		2.1231		

Coefficients and t-statistics (shaded) from estimating Equation 3.7. The full panel is used for this estimation. Significance is listed as ***, **, * for significance on 1%, 5% or 10% level respectively.

[25] A principal component analysis was done to deal with possible collinearity in the model. Most outcomes were robust to this analysis, with the only exception being the interest differential trading in the EURJPY rate, where coefficients changed sign.

The momentum and PPP strategies are significant at a 1% level for all exchange rates and nearly all horizons. The PPP rule is significant for all horizons. The sign of this strategy is as expected for three out of four currencies, thereby stabilizing the exchange rate for those currencies. The PPP rule shows destabilizing behavior for the USDJPY exchange rate. The momentum rule shows stabilizing behavior for the Japanese yen against the euro and the U.S. dollar. In other words, the deviating behavior of traders for the Japanese FOREX market still occurs when regressing the combined model. We can find extrapolative effects for the U.S. dollar against the euro and the pound sterling. A strong pattern is observable for the significance of this rule over forecast horizons. The results clearly indicate that extrapolation becomes weaker and less significant for longer forecast horizons. For the twelve-month horizon, three out of four exchange rates no longer reveal extrapolative expectations. For these horizons, investors believe in UIP for two currencies. The EURJPY is dominated by carry trade, as this coefficient is negative and significant for all horizons.

Numbers can be interpreted as follows: the coefficient of 0.2534 for the EURUSD one-month horizon extrapolative strategy means that speculators expect 25% of the past period price movement to continue in the coming month. The EURJPY twelve month PPP coefficient of 0.2458 indicates that investors believe that, after twelve months, the deviation from the PPP value is reduced by 25%.

As mentioned before, a drawback of the OECD rate is that its frequency (annual) does not correspond to the frequency of our survey data (weekly) and therefore contains less variation. This mismatch between the frequency of the forecasts and the PPP value may lead to the variation of the PPP rule being driven mainly by variation in the spot exchange rate (rather than variation in PPP). Correlations show that there is a certain degree of correlation between the PPP deviation and exchange rate returns. To make sure that this does not drive our results, however, we have run orthogonalized regressions with the series for the PPP rule replaced by the residuals obtained from regressing the PPP rule on the momentum rule of equation (3.9). This does not qualitatively change our results – the signs and significance stay the same[26].

[26] Correlation tables and results from the orthogonalized regressions are available upon request.

When regressing the strategies separately on the expectations, we find that there are two main improvements in the models. Distinguishing between bandwagon and contrarian expectations in the momentum model and distinguishing between carry and UIP traders in the interest model increased the fit of those models. Therefore, it seems appropriate to include these improvements in the combined model as well. Table 3.7 presents the results of regressing Equation (3.8).

We find the results to be comparable to the regressions of the separate strategies and the regression of the combined model. In general, bandwagon and contrarian effects seem to decrease for longer forecasting horizons. The signs for bandwagon effects are as expected, but for contrarian effects, we find significant positive coefficients for the EURUSD one-month and the GBPUSD one- and three-month expectations. This can be caused by the fact that these exchange rates only showed positive returns for the sample period, which could have had an influence on the sentiment of investors. Moreover, the 'short term' for bandwagon effects is usually assumed to be one to three weeks, it is therefore unclear whether the one-month horizon classifies as short or medium horizon. The PPP model shows the expected sign for three out of four currencies. For these currencies, the PPP expectations are stabilizing. Only the EURJPY shows a negative sign, which can be explained by the constant undervaluation of this exchange rate. If a currency is constantly undervalued, investors might adapt their expectations and lose their faith in mean reversion of the exchange rate. For carry and UIP trade, we find the expected signs for all significant coefficients.

3.4.5 Time-varying rules

Until now, we have assumed that agents assign constant weights to the three forecasting rules. In this section, we will change this by estimating Equations (3.9) - (3.11) on the mean expectations using nonlinear least squares. To test the added value of the switching rule, we estimate the model with static weights (Equation (3.7) with mean expectations) before we estimate the dynamic model. The added value is then tested by applying a likelihood ratio test and comparing these results with Chi-squared probabilities.

Table 3.7: Results heterogeneity (extended model)

		c		bandwagon		contrarian		PPP		carry		uip		adj R^2
EURJPY	**1m**	-0.0077	***	0.0595	***	-0.3156	***	0.1244		-0.6193	***	0.1699	***	0.6117
		-5.1395		2.5454		-19.2827		1.4617		-11.042		2.929		
	3m	-0.0191	***	0.0787	***	-0.153	***	0.5754	***	-1.2785	***	0.2587	*	0.5903
		2.4038		2.5971		-6.2161		2.6347		-8.444		1.7588		
	12m	-0.0454	***	0.1647	**	-0.116	***	1.811	***	-2.0345	***	0.4277		0.589
		-3.8131		1.9815		-2.733		3.0675		-4.8258		0.9673		
EURUSD	**1m**	-0.0057	***	0.0393	***	-0.0028		1.0127	***	-0.3033	***	0.2316	***	0.5565
		-3.2064		8.8691		-0.6896		6.2595		-5.5241		4.4035		
	3m	0.0015		0.0405	***	-0.0258	***	0.9026	***	-0.572	***	0.4026	***	0.6022
		0.4453		4.7961		-2.9891		2.4038		-5.113		3.8496		
	12m	0.0324	***	0.0005		-0.1115	***	1.099		-1.0829	***	1.1447	***	0.7137
		3.918		0.0253		-4.5298		1.0207		-2.6237		4.4325		
GBPUSD	**1m**	-0.0218	***	0.0277	***	0.0092		0.305	***	-0.2012	***	0.1322	**	0.5828
		-3.1414		4.6389		1.4831		3.3907		-5.9692		2.0704		
	3m	-0.0027		0.0157	*	-0.0113		0.1269		-0.3435	***	0.3482	***	0.6149
		-0.2604		1.6945		-1.2274		0.7012		-5.7758		2.4793		
	12m	-0.0031		0.0303	*	-0.0164		0.9537	***	-0.2327		0.5335	**	0.6951
		-0.1651		1.8282		-1.0191		2.9286		-1.3855		2.0503		
USDJPY	**1m**	-0.0033	*	0.0541	***	-0.422	***	-0.0464		-0.2289	***	0.2545	***	0.6369
		-1.7152		2.3391		-23.3357		-0.6064		-5.5052		4.977		
	3m	-0.0109	***	-0.0289		-0.3257	***	-0.225		-0.6051	***	0.4476	***	0.5888
		-2.913		-0.8741		-17.1432		-1.5426		-6.6079		4.9721		
	12m	-0.0206	*	0.0354		-0.3182	***	-1.2992	***	-1.0878	***	1.0243	***	0.627
		-1.6703		0.7195		-6.9576		-4.8151		-3.2863		3.0451		

Coefficients and t-statistics (shaded) from estimating Equation 3.8. The full panel is used for this estimation. Significance is listed as ***, **, * for significance on 1%, 5% or 10% level respectively.

Table 3.8: Results heterogeneity on mean expectations (without switching)

		c		momentum		PPP		uip/carry	
EURJPY	**1m**	-0.0275	***	-0.9931	***	0.1063	**	-2.5142	***
		-3.2634		-8.8967		2.312		-2.8624	
	3m	-0.0948	***	-0.1961		0.4336	***	-8.6739	***
		-5.3227		-1.1334		4.4398		-4.751	
	12m	-0.1801	***	0.5228	**	1.0308	***	-12.357	***
		-4.4573		2.1497		5.4435		-2.8919	
EURUSD	**1m**	0.0042	***	-1.0542	***	0.0098		-0.0477	
		2.795		-10.842		0.3049		-0.283	
	3m	0.0145	***	-0.3512	***	0.1505	**	-0.1462	
		4.3807		-2.804		2.1386		-0.3167	
	12m	0.0567	***	-0.26	*	1.1145	***	0.1577	
		9.5245		-1.8081		10.08		0.1679	
GBPUSD	**1m**	0.0014		-0.975	***	0.0204		-0.0765	
		0.79		-15.0011		0.8321		-0.4292	
	3m	0.0105	***	-0.2436	**	0.1684	***	0.0461	
		2.3704		-2.2481		3.0657		0.1034	
	12m	0.0387	***	-0.2587	***	0.722	***	0.2266	
		11.1017		-3.8336		14.7603		0.5496	
USDJPY	**1m**	0.0078	*	-1.2877	***	-0.1435	***	0.6606	***
		1.6936		-15.7577		-3.7214		2.7274	
	3m	0.013		-0.8892	***	-0.3357	***	1.278	**
		1.1524		-7.1133		-3.6143		2.1356	
	12m	0.0387	***	-0.7701	***	-0.9263	***	4.078	***
		2.6025		-4.5643		-6.6027		4.2334	

Coefficients and t-statistics (shaded) from estimating Equation 3.7 on mean expectations with equal weights. Significance is listed as ***, **, * for significance on 1%, 5% or 10% level respectively.

The results can be found in Table 3.8. First, we observe that the results for the non-switching regression with mean expectations do not differ much from the panel regression results discussed in Section 4.4[27]. This indicates that the mean expectation is a good representation of the combined individual expectations, and it is appropriate to use the mean in estimating the weighed function.

The results of estimating the model with time-varying weights are found in Table 3.9. By comparing the estimated coefficients from the static weighing and the dynamic weighing models, we can see that the coefficients are of the same sign under the different models and are of similar magnitude. Therefore, the salient aspects here are the intensity of choice parameter ϱ ('switching') and the weights assigned to the strategies.

A negative intensity of choice parameter means that investors in these markets switch to the rule that generated the lowest forecast error in the previous period. The switching parameter of the EURJPY rate is positive and significant suggesting that investors in this market switch to the rule that generated the largest forecast error in the previous period. Hence, they expect mean reversion at the rule level.

A likelihood ratio test tells us if allowing for switching in the model adds any value to the model with static weights. This is useful, as the intensity of choice parameter is sometimes insignificant because of the non-linear character of the switching (Terasvirta, 1994). The results of this test can be found in the final column of Table 3.9. The outcome of this test can be compared to a Chi-squared distribution to determine whether the log likelihood of the elaborate model is significantly higher than that of the nested model. This is the case for most exchange rates. For the twelve-month horizon, the likelihood ratio test shows us that the dynamic weighting model performs significantly better for all exchange rates. Overall, changing strategy becomes more important as the forecast horizon increases.

[27] Note that the coefficients are three times larger due to the constant weight of 1/3. This also explains why certain coefficients are larger than one.

Table 3.9: Results heterogeneity on mean expectations (with switching)

		c		momentum		PPP		uip/carry		switching		LL w/sw	LL wo/sw	2dLL	
EURJPY	**1m**	-0.0302	***	-0.8053	***	0.1424	***	-2.5068	***	29.1584		714.16	713.03	2.25	
		-3.6168		-5.012		2.9985		-2.9998		0.8964					
	3m	-0.0707	***	0.2715		0.435	***	-4.648	***	17.8676		604.04	595.93	16.22	***
		-4.8368		1.2719		4.148		-3.7844		1.4292					
	12m	-0.1769	***	0.9489	***	1.0258	***	-9.1134	***	12.7768	***	542.67	487.24	110.85	***
		-10.8966		9.2938		9.4404		-8.5358		3.3159					
EURUSD	**1m**	0.0042	***	-1.0778	***	0.0155		-0.0276		-52.9037		713.68	712.42	2.51	
		2.9369		-13.7345		0.4912		-0.1785		-0.808					
	3m	0.0143	***	-0.3764	***	0.1394	*	-0.1609		-37.4467		591.14	591.13	0.03	
		4.2178		-3.1644		1.7831		-0.3372		-0.3283					
	12m	0.0546	***	-0.2118	*	0.9762	***	0.1005		11.5904		557.18	552.56	9.25	***
		8.1243		-1.648		7.9324		0.0895		1.312					
GBPUSD	**1m**	0.0014		-0.9727	***	0.0205		-0.0773		9.2784		737.11	737.10	0.03	
		0.8006		-15.1939		0.8344		-0.4419		0.1544					
	3m	0.0106	**	-0.1325		0.1234	***	0.352		454.3889		614.31	613.57	1.48	
		2.3165		-0.8295		2.3964		0.8401		0.7136					
	12m	0.0351	***	-0.2212	***	0.5733	***	0.3607		16.2669		657.91	649.53	16.75	***
		9.1905		-3.4058		7.4424		0.8678		1.5372					
USDJPY	**1m**	0.0073	*	-1.3118	***	-0.1373	***	0.6343	***	-24.7808		716.29	715.47	1.64	
		1.6604		-17.7188		-3.5406		2.7125		-0.8455					
	3m	0.0118		-0.998	***	-0.3359	***	1.1728	**	-20.6565		583.04	582.17	1.73	
		1.0896		-6.5137		-3.161		2.0339		-1.4959					
	12m	0.0303	***	-1.011	***	-0.9425	***	3.4927	***	-7.723	*	498.45	492.20	12.52	***
		2.5306		-5.8085		-4.1296		4.0492		-1.661					

Coefficients and t-statistics (shaded) from estimating Equation 3.9 on mean expectations. Significance is listed as ***, **, * for significance on 1%, 5% or 10% level respectively.

Table 3.10: Descriptive statistics of the estimated weights

		mean			maximum			minimum			st. dev		
		mom	**PPP**	**UIP**	**mom**	**PPP**	**UIP**	**mom**	**PPP**	**UIP**	**mom**	**PPP**	**UIP**
EURJPY	**1m**	0.3	0.321	0.379	0.436	0.371	0.459	0.224	0.235	0.308	0.038	0.026	0.028
	3m	0.307	0.322	0.371	0.312	0.346	0.406	0.294	0.289	0.348	0.003	0.018	0.017
	12m	0.276	0.331	0.393	0.323	0.457	0.498	0.225	0.192	0.315	0.023	0.078	0.058
EURUSD	**1m**	0.302	0.355	0.343	0.333	0.38	0.345	0.277	0.328	0.339	0.012	0.011	0.001
	3m	0.274	0.374	0.352	0.337	0.423	0.359	0.224	0.321	0.341	0.023	0.021	0.004
	12m	0.063	0.561	0.376	0.496	0.716	0.463	0.001	0.202	0.283	0.112	0.122	0.043
GBPUSD	**1m**	0.343	0.327	0.33	0.346	0.33	0.33	0.34	0.324	0.33	0.002	0.002	0
	3m	0.364	0.31	0.325	0.375	0.326	0.327	0.352	0.298	0.323	0.006	0.007	0.001
	12m	0.172	0.426	0.402	0.217	0.453	0.409	0.142	0.389	0.393	0.019	0.016	0.004
USDJPY	**1m**	0.332	0.334	0.33	0.337	0.337	0.33	0.328	0.332	0.33	0.002	0.001	0
	3m	0.297	0.357	0.346	0.382	0.431	0.398	0.227	0.292	0.293	0.03	0.033	0.024
	12m	0.267	0.37	0.363	0.348	0.47	0.416	0.208	0.276	0.311	0.03	0.056	0.032

Table 3.11: Correlations between strategy weights

		mom-PPP	mom-int	int-PPP
EURJPY	**1m**	-0.67	-0.72	-0.032
	3m	-0.394	0.215	-0.982
	12m	-0.909	0.828	-0.986
EURUSD	**1m**	-0.996	-0.696	0.625
	3m	-0.988	-0.599	0.471
	12m	-0.935	0.041	-0.393
GBPUSD	**1m**	-0.998	0.101	-0.164
	3m	-0.997	0.874	-0.908
	12m	-0.988	-0.777	0.671
USDJPY	**1m**	-0.788	-0.43	0.464
	3m	-0.696	-0.287	-0.489
	12m	-0.894	0.621	-0.907

We can see the evolution of weights for the twelve-month forecasts in Figure 3.2. The graphs show variations in the weights for most of the currencies. Although the PPP rule has lost popularity for the EURJPY rate in the last few years, it has increasingly been used for the EURUSD and the GBPUSD. Although the absolute changes in weights appear relatively small, note that the relative changes are substantial. Furthermore, the analyses are done in a panel setup and, therefore, represent the average. As such, small deviations have a potentially large impact on the market itself.

The descriptive statistics of the weights are displayed in Table 3.10. We can see that in the majority of the cases the weight assigned to the momentum rule declines as the forecast horizon increases. The opposite occurs for the PPP forecasting rule. This is in line with theory, as it is assumed that (positive) feedback trading mainly occur at short horizons, and forecasting based on PPP is more applicable for longer horizons (as it takes a long time before the exchange rate reverts to the value suggested by the purchasing power parity). We can also see that the standard deviation of the weights increases with forecasting horizon.

Finally, it would be interesting to see between which strategies most switching takes place. We can evaluate this by looking at the correlations between the weights of the different strategies. The results are shown in Table 3.11. For all currencies and horizons, we find a negative correlation between momentum traders and PPP traders; thus, the switching more often occurs between these strategies. Switching between the other strategies is not that straightforward. In the short term, switching also appears to occur between momentum traders and interest traders. However, in the long term, agents particularly switch between PPP traders and interest traders.

3.5 Conclusion

In this chapter, we used survey expectations for four exchange rates to evaluate the way in which investors form their expectations, building on the theoretical framework of the heterogeneous agent literature. To do this, we tested three different strategies on the disaggregated expectations: momentum trading, PPP trading and interest trading strategies. The momentum rule was divided into bandwagon and contrarian expectations, and the interest trading strategy was divided into UIP and carry trade expectations. These extensions to the basic models have shown to be a valuable improvement to the models. After testing the strategies separately and in a combined model the survey expectations were evaluated to determine whether agents switch between strategies over time.

We obtained significant results for all strategies when tested separately and when tested in a combined model. This implies that investors use past changes, PPP rates and interest rates in forming their expectations. Momentum trading especially occurs for short horizons, whereas PPP trading is more common for longer horizons. The interest differential is used on all horizons but primarily for long-horizon forecasting. We find indications that agents have a stronger tendency to apply a carry trade (UIP) expectation at the shorter (longer) forecast horizon. Interestingly, there are also differences in expectations within different strategies. Some people expect past trends to continue and therefore positively extrapolate past returns into future forecasts (bandwagon). Other investors expect past trends to revert. There are investors who use the interest differential as a tool for carry trade; that is, they expect an appreciation of the currency of the high-interest-rate country. There are also investors who believe in UIP and therefore expect a depreciation of the currency of the high-interest-rate country. Furthermore, a long history of positive returns seems to influence investors when forming their expectations, making them more vulnerable to bandwagon expectations. A long history of undervaluation of an exchange rate can cause a loss of faith in reversion to the fundamental value.

Not only do investors use different strategies to form their expectations, they also change the weights they assign to these strategies based on the past forecasting accuracy of the strategies. The weight assigned to the extrapolative strategy decreases for longer horizons, and investors put more weight on PPP rates in this case. Investors switch more for longer forecasting horizons. Switching mainly occurs between momentum traders and PPP traders.

Our results further indicate that investors have deviating ways of forming expectations for the exchange rates that involve the Japanese yen. For the momentum and the PPP rules, we found surprising results that contradict earlier works as well as our empirical findings for the other exchange rates. This might suggest that Japan can be seen as a separate case. One of the reasons for this can be that Japan is an export economy and therefore the Japanese government actively intervenes in the foreign exchange market to maintain their trading competitiveness, which makes conventional rules less useful. Further research could explore this phenomenon.

The results we presented in this chapter are, on the one hand, a strong confirmation of theoretical statements and empirical findings from the behavioral finance literature. On the other hand, they are also an extension to the literature, as we have shown that there is also important heterogeneity within the strategies. Future research could investigate this heterogeneity and its implications for exchange rates. It would also be interesting to see whether these findings apply to other asset classes. Furthermore, applying the model to different time periods and/or focusing on different crises could provide better insight into the effect of heterogeneity and switching on crises and vice versa.

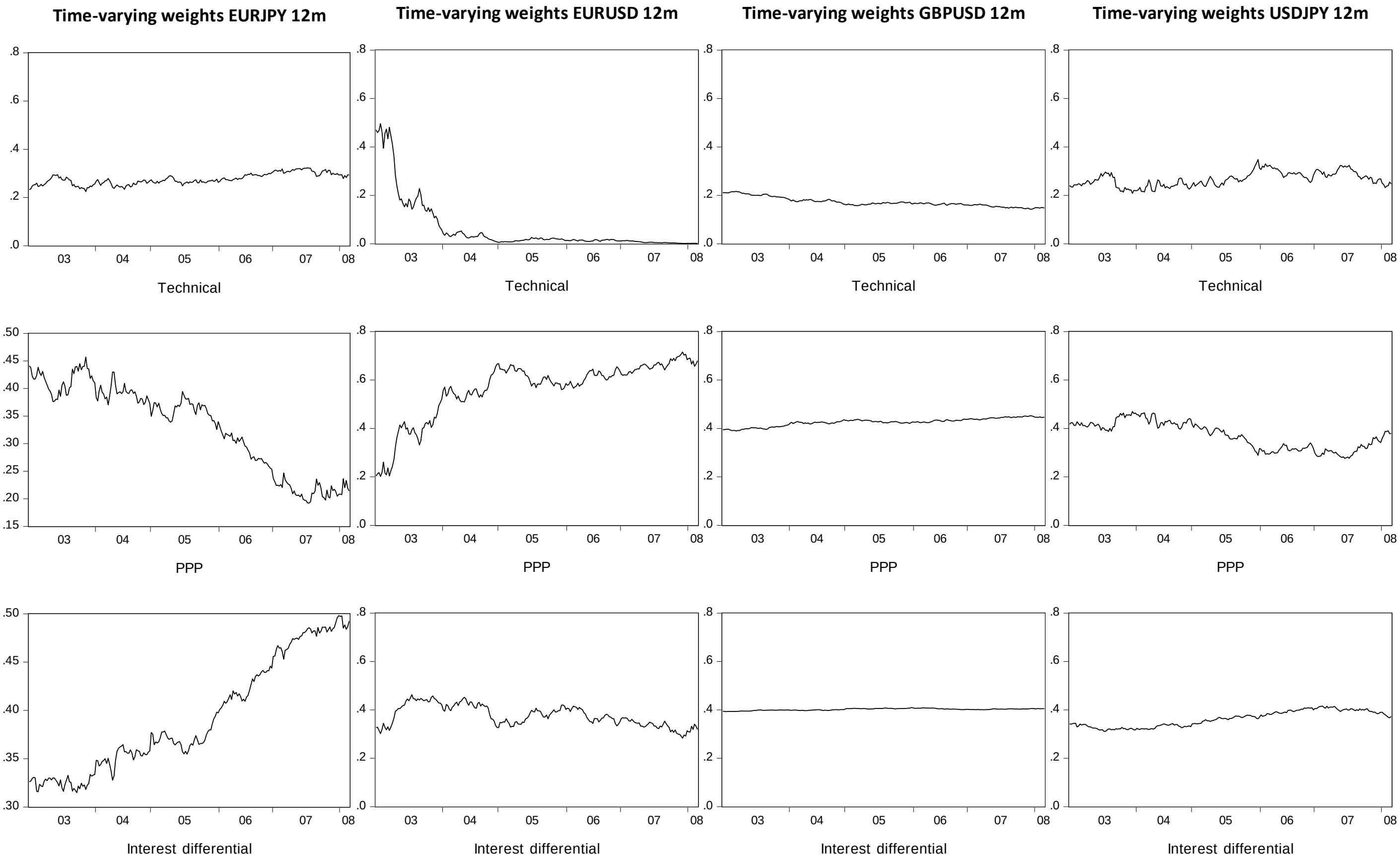

Figure 3.2 Time varying weights for momentum (technical), PPP, and interest differential strategies, 12 month forecasting horizon.

Fear or fundamentals?

4 Heterogeneous beliefs in the European sovereign CDS market[28]

4.1 Introduction

Motivated by the ongoing turmoil in international debt markets and the development of the European sovereign debt crisis following the Global Financial Crisis (GFC), this chapter examines if the interaction of market fundamentals and momentum played a significant and potentially destabilizing role on sovereign CDS spread movements over the recent crisis period. Sovereign credit risk has come to the forefront of market participants' concerns as recent crises have shown that well-developed countries are also prone to this risk and can also default on their liabilities. This concern is observable in the recent movements of sovereign credit default swap (CDS) spreads. For instance, as illustrated in Fig. 4.1, the CDS spreads for Eurozone countries were ranging from historically low levels of around 2 bps (for Germany) and 13 bps (for Greece) at the beginning of 2006 but had risen to levels of 25 bps and an alarming 270 bps, respectively, by the initial stages of the European Debt Crisis in early 2010. Cross-sectional differences in sovereign CDS spreads have also magnified, as the spreads of certain peripheral countries in the Eurozone such as Ireland and Greece increased much more dramatically than the spreads of core Eurozone countries such as Germany and the Netherlands. Various authors explain this development as being due to global risk repricing

[28] This chapter is based on "Chiarella, C., S. ter Ellen, X. He, E. Wu (2014), Fear or Fundamentals? Heterogeneous Beliefs in the European Sovereign CDS Market, Journal of Empirical Finance." It was partly written while Saskia ter Ellen was visiting University of Technology Sydney (UTS) Business School. We would like to thank the editor, two anonymous referees, Remco Zwinkels, seminar participants at the University of Technology Sydney, University of Groningen, VU University Amsterdam, Norges Bank, and Australian National University, and participants of the 2013 Auckland Finance Meeting, the 2013 meeting of the Society of Nonlinear Dynamics and Econometrics (SNDE), the Southampton International Conference on the Global Financial Crisis, the 11th INFINITI conference on "The Financial Crisis, Integration and Contagion" and the "Nederlandse Economen Dag" (Dutch Economists Day) for their useful comments.

and increased risk aversion of international investors combined with weakening macroeconomic factors (Sgherri and Zoli, 2009; Attinasi et al., 2009; Gerlach et al., 2010; Caceres et al., 2010).

In this study, we investigate whether the high sovereign credit spreads observed across Europe since the onset of the international crisis period were completely driven by (macroeconomic) fundamentals or were rather a result of the interaction of market fundamentals and momentum. Using a sample of thirteen European countries, of which ten are officially part of the European Monetary Union (EMU), we examine whether the widespread escalation in sovereign CDS spreads were the amplification effects of weakened fundamentals interacted with increasing market-wide momentum, while controlling for changes in global risk (re)pricing. In doing so, we uncover new evidence that indicates market momentum became more pervasive in sovereign CDS markets from 2007-2013. The dominant effect of momentum was magnified in peripheral Eurozone countries as mean reversion to fundamentals remained largely absent from the sovereign CDS markets for Greece, Hungary, Ireland and Portugal. In the core Eurozone countries, some of the recent movements in sovereign CDS spreads can be explained by the strains on fundamentals from having to support a weakening EMU and particularly the small group of troubled peripheral sovereigns, but we reveal that momentum has also played a large role in amplifying and destabilizing sovereign CDS spreads since the GFC.

The remainder of the chapter is organized as follows. Section 2 summarizes the related literature. Section 3 explains how we calculate fundamental values for the different countries' sovereign CDS spreads. Section 4 describes the data used in our empirical analyses and Section 5 describes the heterogeneous agent model that we use to explain the large movements in sovereign CDS spreads from 2007 onwards and how it is estimated. Section 6 gives an overview and interpretation of our estimation results, and Section 7 concludes.

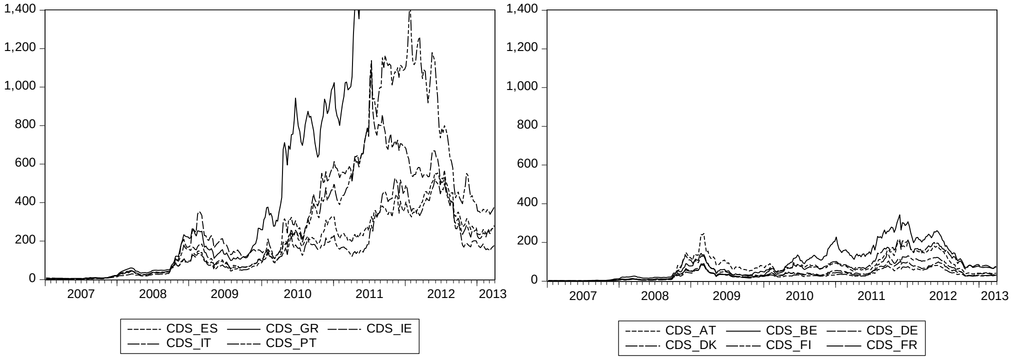

Figure 4.1. The sovereign CDS spreads of eleven countries from our sample grouped as either 'peripheral' or 'core' countries. The group of peripheral countries consists of Greece (GR), Ireland (IE), Italy (IT), Portugal (PT) and Spain (ES). The group of core countries consists of Austria (AT), Belgium (BE), Denmark (DK), Finland (FI), France (FR) and Germany (DE). Note that the scaling of both graphs is equal to facilitate comparison.

4.2 Related literature

It is important to understand the market dynamics of sovereign credit markets as escalations in governments' borrowing costs have undesirable welfare implications. This chapter proposes a simple model of heterogeneous expectations on market fundamentals and momentum to explain the dynamics of such markets.

The literature traditionally relied on country fundamentals to predict sovereign risk levels but has struggled in recent years to explain the increasingly substantial deviations of actual market spreads from those implied by macroeconomic fundamentals. For instance, Arghyroua and Kontonikas (2012), Beirne and Fratzscher (2012) and Ghosh et al. (2013) all find that before the crisis, spreads were too low, and the market pricing of sovereign risk was not fully reflecting fundamentals but rather international risks. However, recent works have also documented that the crisis led to a renewed interest in country-specific economic fundamentals for European economies (Mody, 2009; Jaramillo and Weber, 2012). Whilst various non-fundamental based explanations have been provided, there remains a gap in the current understanding on the exact cause of the recent debt market turmoils in Europe. For example, Aizenman et al. (2013) find that spreads of European periphery countries were too high given fiscal space and other macroeconomic fundamentals, suggesting that these economies switched to a "pessimistic self-fulfilling expectational equilibrium". De Grauwe and Ji (2013) offer a similar interpretation by saying that the surge in spreads during 2010-11 was associated with "negative self-fulfilling market sentiments". Badaoui et al. (2013) agree that spreads were not fully reflecting fundamentals during the crisis but argue that the increase in CDS spreads during the crisis was caused by a surge in liquidity and demand for credit protection. Despite the general agreement on the inability of fundamental forces to fully account for recent sovereign credit spread movements, there is conflicting evidence regarding the non-fundamental based explanations.

We contribute to the debate on what has driven country spreads by providing a heterogeneous behavioral explanation for the escalation of the European Debt Crisis. Our main hypothesis is that market momentum, together with its interaction with fundamentals, played a dominant role in driving up CDS spreads of particularly the peripheral Eurozone countries beyond the levels warranted by their weakened economies. To date, there has not been a suitable theoretically motivated framework used to formally test this.

This chapter is closely related to the literature on financial bubbles and momentum (in both time series and cross-section). It is generally understood that in many asset markets there can be large and persistent deviations from fundamentals from time to time. Moreover, short-run momentum is also well documented in financial markets (Balvers and Wu, 2006, Moskowitz, Ooi and Pedersen, 2012, and Asness, Moskowitz and Pedersen, 2013). The persistent deviations and trading activities in asset markets based on short-run momentum typically lead to so-called financial market bubbles. Specifically, Allen and Gale (2000) and Baker and Wurgler (2007) model this for equity markets; Frankel and Froot (1990b) for foreign exchange markets and Case and Shiller (2003) do so for the housing market. The time-varying effect of fundamentals on sovereign CDS spreads documented in the current literature suggests that the pricing of credit risk in the European Union has important similarities to the assessment of risk and returns in other asset markets. In particular, there is anecdotal evidence that after the initial revelation of serious debt problems in some EMU members, some bond market specialists became very concerned and openly expressed their doubts regarding the ability of market participants to correctly price (sovereign) credit risk. Disregarding the European 'no-bailout clause' (i.e. article 125 of the 'Treaty on the functioning of the European Union'), investors appear to have been overly optimistic pre-crisis about the economic and financial health of all Eurozone countries and the stability of the monetary union. Thus, it can be viewed that sovereign credit markets across Europe exhibited bubble-like behavior, with persistent under-pricing of sovereign credit risk pre-crisis and overpricing of credit risk post-crisis possibly due to momentum trading activity.

Our approach to capture this behavior in European sovereign CDS markets is largely motivated by successful descriptions and explanations of heterogeneous agent models for bubble-like behavior in a variety of other financial markets. Generally, traditional finance models where representative traders (agents) have homogeneous and rational expectations perform quite poorly in explaining the above described process. Models that relax those assumptions and introduce boundedly rational heterogeneous agents have evolved over the past three decades (Frankel and Froot, 1990a; Chiarella, 1992; Brock and Hommes, 1997, 1998; Lux, 1998; Chiarella and He, 2003b; and De Grauwe and Grimaldi, 2006). These models assume that investors have heterogeneous expectations and are boundedly rational in the sense that they choose from a set of rules of thumb in order to form expectations about future asset prices. In most applications, two types of agents are distinguished. One type uses historical price movements to predict future returns and is commonly referred to as chartists (akin to momentum traders). The second type believes in a mean reversion of the market price to the fundamental value and is therefore generally referred to as fundamentalists. Complicated market dynamics occur when agents assess the relative performance of the two rules and some choose to switch to a better performing rule. These models have been successfully used to (empirically) explain speculation and bubble-like behavior in, for instance, stock markets (Boswijk et al., 2007; He and Li, 2007, Chiarella et al, 2012, 2013), foreign exchange markets (De Jong et al., 2010; Ter Ellen et al., 2013), option markets (Frijns et al., 2010), housing markets (Kouwenberg and Zwinkels, 2013) and oil markets (Ter Ellen and Zwinkels, 2010). In this chapter we follow the same approach to describe the expectations and pricing of sovereign credit risk, measured by CDS spreads, within the EMU. Agents use a weighted average of fundamental and momentum strategies when forming their expectations of the future CDS spreads. In aggregation, the market allocates time-varying weights to the two strategies, depending on the relative performance of these strategies. We model sovereign CDS spreads as they are accepted in the extant literature to be a pure measure of credit risk and thus should reflect the market's aggregate opinion on the price that is commensurate with taking on the sovereign obligor's underlying default risk (Badaoui et al., 2013). This is because CDS contracts are derivative instruments designed to provide insurance against credit events such as sovereign defaults or debt restructurings (Longstaff et al., 2011).

To the best of our knowledge, this chapter is one of the first to introduce a heterogeneous beliefs structure into the sovereign CDS market. Xiong and Yan (2010) introduce disagreement between two types of agents about future economic conditions to explain several stylized facts in the bond markets. They find that bond yield volatility is increased due to the changes in wealth of the two speculating parties. They emphasize the importance of modelling a pricing model with heterogeneous beliefs and show that the results can only be obtained in a model with a representative agent under very strong assumptions. Blommestein et al. (2012) empirically investigate to what extent bond market participants in the CDS market are rational and conclude that it is more likely that they are boundedly rational. They distinguish between two regimes, where CDS spreads reflect credit risk correctly based on fundamentals in one regime, and credit risk is priced based on sentiment in the other regime. This chapter follows a similar approach but has the advantage of being able to realistically capture the dynamic switching behavior of the market between fundamentals or momentum based on their recent forecasting performance through the discrete choice model instead of relying on stochastic switching functions.

4.3 Fundamental default spread

The price of a CDS contract (often referred to as the 'CDS spread') is understood to consist of a compensation for default (hereafter referred to as the 'fundamental default spread') and an extra premium, often referred to as the 'credit risk premium'. The fundamental default spread would be easy to calculate if one knew a country's true default probability. However, usually we are not sure about the default probability and have to model the spread under certain assumptions.

Models for pricing credit risk can be generally divided into two groups, structural models (based on Merton, 1977) and reduced-form (also referred to as intensity-based) models. Both of these models are commonly used for pricing corporate CDS spreads. However, structural models are generally considered to be less suitable for sovereign credit spreads because they rely on estimates of levels and volatilities of equity and debt market values, which are not easily obtained for countries. Alternatively, reduced-form/intensity-based models (Duffie, 1999; Hull and White, 2000; Duffie and Singleton, 2003; to name a few important contributions) obtain a CDS spread by equalizing the expected payments and expected payoff to solve for the annualized premium (spread). The expected value mainly depends on the recovery rate and the (risk-neutral) hazard rate. In order to obtain a fundamental default spreadas input for our model, we follow the theoretical models of Duffie (1999) and Duffie and Singleton (2003) for pricing credit default swaps.

Duffie (1999) models the spread of a credit default swap as a function of the present value of the payments and the present value of the payoffs of the contract, conditional on a risk-neutral hazard rate. The market value of the swap is a function of default parameters *h* and *f*:

$$V(h, f, T, U) = B(h, T)f - A(h, T)U \tag{4.1}$$

where U is the market default swap spread, f is the loss of face value at default, $A(h, T)$ is the price of an annuity of 1 unit paid at each coupon date until default or maturity $T(n)$ and $B(h, T)$ is the market value of a payment of 1 unit at the first coupon date after default, provided the default date is before maturity date $T(n)$. Functions $A(h, T)$ and $B(h, T)$ are given by:

$$A(h, T) = a_1(h) + \cdots + a_i(h) \tag{4.2}$$

$$a_i(h) = exp\{-[h + y(i)]T(i)\} \tag{4.3}$$

$$B(h, T) = b_1(h) + \cdots + b_i(h) \tag{4.4}$$

$$b_i(h) = exp[-y(i)T(i)]\,\{exp[-hT(i-1)] - exp[-hT(i)]\} \tag{4.5}$$

where $T(i)$ is the time of the ith coupon date to maturity and $y(i)$ is the continuously compounding default-free zero-coupon yield to the $i - th$ coupon date. In words, $a_i(h)$ is the value at time zero of receiving 1 unit of account at the $i-th$ coupon date in the event that default is after that date and $b_i(h)$ is the value at time zero of receiving 1 unit of account at the $i-th$ coupon date in the event default is between the $(i-1)-th$ and the ith coupon date. Hence, we can obtain the at market default swap spread $U(h,t,f)$ by solving $V(h,f,T,U)=0$ for U:

$$U(h,t,f)=\frac{B(h,T)f}{A(h,T)} \tag{4.6}$$

The most crucial element in this CDS pricing formula is the risk-neutral hazard rate $h, which$ is the arrival rate of the credit event. In a risk-neutral world the hazard rate is 0.01, or 100 basis points in the case that a credit event occurs once every hundred years. Several approaches for obtaining this element have been taken.

As a proxy for the risk-neutral probability of default h, Hull and White (2000) use bond prices based on arbitrage arguments. There are several arguments for why we do not use this approach here. First of all, sovereign yield spreads reflect not only credit risk, but also other factors such as liquidity (risk), tax regulation, and so forth. Secondly, our objective is to find the fundamental default spread, and not just the "arbitrage-free" spread. Using input from the underlying sovereign bond market to do this rests on the assumptions that credit risk is appropriately priced in the bond market. This is a big leap of faith when there is much evidence showing that price discovery actually occurs in CDS markets (Blanco et al. 2005; Forte and Pena, 2009 and Palladini and Portes, 2011). Moreover, speculation about sovereign credit risk (which we conjecture has played a role in recent debt market turmoils) will be more apparent in the CDS market where there is a price (risk premium) paid to ensure against default (a credit event).

Another way of obtaining the risk-neutral probability of default is by using the historical probability of default as a proxy. However, as Duffie and Singleton (2003) point out: "differences between actual and risk-neutral default probabilities reflect the risk premia required by market participants to take on the risk associated with default". The historical probability of default will therefore most likely underestimate the risk-neutral probability of default, which is needed for CDS pricing. More importantly, for our sample of European countries there does not exist a very rich history of default in recent decades making this an inferior approach.

The available approaches to obtaining risk-neutral probabilities of default do not seem to be appropriate for calculating fundamental default spreads. To overcome this problem, we develop a new approach that combines methods from the theoretical literature on CDS pricing with methods from empirical works through the following three key steps.

First, the formulas for pricing CDS spreads (Eq. (4.1)-(4.6)), in combination with market data on CDS spreads, are used to back out the implied risk-neutral hazard rate h (Duffie, 1999). We do this for every week and each country in our sample. This yields a panel of 'market-based hazard rates' h_t.

Secondly, the panel of market-based hazard rates is regressed on a set of fundamental factors drawn from the country risk literature that are known to affect a country's probability of default. These factors are further explained in Section 4.

Thirdly, the predicted hazard rates resulting from regressing h_t on the set of fundamental variables, are then used in the original CDS pricing formula to back out the fundamental default spreads, i.e., a fitted spread based on purely fundamental factors[29].

4.4 Data and fundamental variables

4.4.1 Data description

Our sample consists of weekly data covering thirteen countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Poland, Portugal and Spain) from January 2004 to April 2013. The selection of these countries is mainly based on data availability. First, we selected all European Union countries for which sovereign CDS spreads were available in our dataset from the beginning of 2004. We then discarded all countries for which one or more of the selected macroeconomic variables used to obtain the fundamental default spreads were not available for the full sample period. Our sample comprises 13 members of the European Union of which ten countries are also part of the

[29] Note that it is impossible to include all possible fundamental variables in this analysis, so that our fundamental default spread should be viewed as the average default spread given a set of fundamentals that are commonly used in the current literature. We thank an anonymous reviewer for pointing this out.

Eurozone (including the five 'troubled' periphery countries: Greece, Ireland, Italy, Portugal and Spain) and three countries (Denmark, Hungary and Poland) are not.

Following prior studies, we also restrict our sample to sovereign CDS spreads on contracts denominated in US dollars with a five-year maturity provided by the Markit group. The five year maturity segment is commonly used as it is deemed to be the most liquid of all tenors (see Longstaff et al., 2011, Fender et al., 2012 and Remolona et al., 2008a,b). The CDS spreads, being the annual payment made for having a long position in a CDS contract, are weekly averages expressed in basis points (bps). Descriptive statistics for the sovereign CDS spreads can be found in Table 4.1.

4.4.2 Estimating the probability of default

We first obtain estimates for a country's probability of default as the input for our fundamental default spread calculation. The statistics of the estimated fundamental spreads are summarized in Table 4.2. To estimate the risk-neutral probability of default based on the implied hazard rates, we consider a comprehensive list of traditional default determinants from the empirical sovereign credit risk pricing literature. There exists an extensive literature investigating the relation between sovereign credit spreads and (macro) economic fundamentals, and there are many potential determinants. Hence, we consider explanatory variables that have featured in several recent papers, selected on the basis of relevance for our sample European countries. These include the comprehensive study of Longstaff et al. (2011), which accounts for a number of global, regional and country-specific factors; the work of Dieckman and Plank (2012), which specifically looks at default risk in developed countries, and Hilscher and Nosbusch (2010), who also predict probabilities of default with a number of fundamental factors. Guided by the current literature, we include the following fundamental variables that have been documented to have a significant impact on country CDS spreads and/or probabilities of default.

Table 4.1: Descriptive statistics of market sovereign CDS spreads

	Austria	Belgium	Germany	Denmark	Spain	Finland	France	Greece	Hungary	Ireland	Italy	Poland	Portugal
							2004-2013						
Mean	48.34	64.82	25.28	31.1	118.99	21.33	44.75	751.43	187.71	184.83	115.28	89.64	230.69
Max	246.25	342.59	104.02	141.28	568.63	85.93	216.94	21681.29	644.71	1116.57	526.32	383.48	1473.75
Min	1.44	1.88	1.44	1.17	2.25	1.17	1.47	4.57	9.51	1.65	5.7	7.59	3.78
St.Dev.	56.11	80.95	27.21	37.59	146.1	22.26	55.6	2196.52	173.7	244.16	139.45	81.42	349.32
Skew	1.11	1.32	1.06	1.33	1.13	1.07	1.36	5.01	0.63	1.27	1.34	0.93	1.63
Kurt	3.41	3.76	3.14	3.6	3.18	3.17	3.92	34.8	2.15	3.44	3.79	3.14	4.5
							2004-2007						
Mean	2.59	2.85	3.03	2.66	3.34	2.92	2.97	10.86	24.31	2.88	9.25	19.48	6.25
Max	3.38	3.85	4.5	3.43	4.17	3.79	4.06	17.06	49.47	4.13	14.73	40.15	9.36
Min	1.59	2.23	1.5	1.45	2.25	1.66	1.6	7.04	9.51	1.65	6.97	9.16	4.77
St.Dev.	0.42	0.46	0.78	0.45	0.55	0.55	0.77	2.51	8.66	0.54	1.83	7.23	1.25
Skew	-0.19	0.78	-0.33	-0.94	-0.42	-0.65	-0.08	0.43	0.66	-0.05	1.02	1.34	1.02
Kurt	2.71	2.23	1.99	3.78	1.71	2.73	1.55	1.94	2.74	1.89	3.17	3.71	3.01
							2007-2013						
Mean	70.16	94.39	35.89	44.66	174.17	30.11	64.68	1176.15	265.65	271.64	165.87	123.1	337.76
Max	246.25	342.59	104.02	141.28	568.63	85.93	216.94	21681.29	644.71	1116.57	526.32	383.48	1473.75
Min	1.44	1.88	1.44	1.17	2.33	1.17	1.47	4.57	16.96	1.83	5.7	7.59	3.78
St.Dev.	56.35	83.52	27.3	38.96	148.67	22.21	57.76	2665.57	160.33	254.45	144.23	79.37	380.55
Skew	0.65	0.86	0.58	0.87	0.64	0.62	0.89	3.95	0.11	0.77	0.88	0.49	1.1
Kurt	2.81	2.78	2.54	2.53	2.41	2.55	2.88	22.64	2.15	2.43	2.77	2.91	2.95

Table 4.2: Descriptive statistics of fundamental sovereign CDS spreads

	Austria	Belgium	Germany	Denmark	Spain	Finland	France	Greece	Hungary	Ireland	Italy	Poland	Portugal
							2004-2013						
Mean	43.62	60.16	42.76	25.15	55.14	32.49	45.27	619.96	143.28	97.18	138.43	59.4	129.54
Max	158.37	170.88	120.11	77.01	257.74	89.81	122.13	3143.69	397.44	398.03	372	146.86	514.93
Min	2.03	2.85	2.09	1.57	1.71	2.18	1.98	9.31	12.46	1.32	7.9	7.46	4.12
St.Dev.	42.63	57.09	40.99	23.42	69.33	27.95	43.68	901.6	118.37	128.44	126.85	47.48	159.14
Skew	0.4	0.19	0.2	0.2	1.41	0.21	0.18	1.42	0.21	1.13	0.23	0.13	1.12
Kurt	1.79	1.29	1.3	1.32	4.18	1.39	1.24	3.51	1.36	2.71	1.32	1.23	2.81
							2004-2007						
Mean	3.07	3.91	3.18	2.28	2.37	5.1	2.74	15.92	28.64	1.87	16.07	11.83	6.83
Max	6.87	6.72	5.2	4.59	3.99	15.31	4.61	36.63	75.97	2.87	37.32	18.57	17.89
Min	2.03	2.85	2.09	1.59	1.71	2.18	1.98	9.31	12.46	1.32	7.9	7.46	4.12
St.Dev.	1.15	0.91	0.83	0.72	0.59	3.02	0.65	6.22	13.29	0.33	6.83	2.3	3.44
Skew	1.92	1.37	0.75	1.95	1.06	1.68	1.38	1.9	1.18	1.12	1.44	0.58	2.04
Kurt	5.66	3.93	2.44	5.86	3.21	5.15	4.2	5.72	3.93	3.87	4.41	2.82	6.2
							2007-2013						
Mean	62.97	86.99	61.65	36.07	80.32	45.55	65.55	908.11	197.97	142.65	196.8	81.35	188.07
Max	158.37	170.88	120.11	77.01	257.74	89.81	122.13	3143.69	397.44	398.03	372	146.86	514.93
Min	2.21	2.98	2.19	1.57	2.03	2.6	2.18	12.14	19.75	1.4	14.52	7.55	5.51
St.Dev.	39.04	50.82	37.11	20.99	71.68	24.92	39.28	971.59	106.49	134.05	114.83	42.02	163.7
Skew	-0.3	-0.69	-0.67	-0.68	0.98	-0.62	-0.71	0.88	-0.64	0.58	-0.61	-0.76	0.6
Kurt	2.28	2.01	1.98	2.05	3.14	2.07	1.93	2.2	2.04	1.76	1.89	2.03	1.91

Table 4.3: Variable descriptions

Variable	Description	Source	Original freq	Calculation	Conversion
CDS	CDS spreads (bps)	Markit	daily		weekly average
CCR	Sovereign credit rating scores	S&P/Moody's/Fitch	daily	ratings from 0 (default) to 20 (AAA or similar)	end of week value
debtgdp	Debt/GDP ratio	Eurostat	annual		constant until new value
totvol	Terms of trade volatility	IMF-IFS	annual	export-PI/import-PI; historical vol past 5y	constant until new value
stmret	Local stock market returns	MSCI	daily	log returns	aggregate
stmvol	Local stock market return volatility	MSCI	daily	90d rolling window historical vol	aggregate
locfin	Local financials index	Datastream	daily	log returns	end of week value
dba	Domestic bank assets	ECB	monthly	log returns	constant until new value

The table gives an overview of the variables used for estimating the implied hazard rate in Equation 4.7 based on weekly data, and the conversion of those variables from daily, monthly, or annual frequency to weekly frequency.

Table 4.4: Descriptive statistics of the fundamental variables

	Austria	Belgium	Germany	Denmark	Spain	Finland	France	Greece	Hungary	Ireland	Italy	Poland	Portugal
							CCR score						
Mean	19.95	18.73	20	20	18.54	20	19.94	12.05	12.71	17.67	16.66	14.11	15.7
Max	20	19	20	20	20	20	20	16	14.67	20	18	14.33	18
Min	19.67	17.67	19.83	20	11.17	19.83	19.33	0.67	9.67	11.67	13	13.67	9
St.Dev.	0.11	0.44	0.02	0	2.55	0.02	0.16	5.17	1.7	3.27	1.4	0.31	3.32
							Debt-to-GDP						
Mean	66.21	92.92	70.99	39.35	49.73	42.54	71.52	121.21	70.09	51.22	109.97	49.23	77.29
Max	73.4	99.6	82.4	47.2	84.2	53	90.2	170.3	81.8	117.6	127	56.2	123.6
Min	60.2	84	64.4	27.1	36.3	33.9	63.3	97.4	58.6	24.6	103.3	45	59.4
St.Dev.	4.15	4.64	6.52	6.65	11.68	5.23	8.81	23.64	8.89	31.02	7.23	3.87	16.9
							Stock market volatility						
Mean	0.0155	0.0119	0.0127	0.0117	0.014	0.0159	0.0128	0.0189	0.0175	0.0165	0.0133	0.0147	0.0107
Max	0.0497	0.0381	0.0342	0.0361	0.0363	0.0347	0.0362	0.0394	0.0478	0.0539	0.0355	0.0321	0.0292
Min	0.006	0.005	0.0059	0.0052	0.0056	0.007	0.0056	0.0071	0.0095	0.0059	0.0048	0.0067	0.0035
St.Dev.	0.0088	0.0066	0.0059	0.0059	0.007	0.0062	0.0062	0.009	0.0075	0.0097	0.0072	0.0054	0.0054
							Stock market returns						
Mean	-0.0001	0.0003	0.0008	0.0021	-0.0001	-0.0005	0.0003	-0.003	0.0009	-0.0017	-0.0012	0.0008	-0.0006
Max	0.1324	0.106	0.1093	0.1255	0.1221	0.1122	0.1096	0.1528	0.1656	0.1729	0.1161	0.1384	0.0821
Min	-0.2048	-0.2231	-0.1649	-0.1805	-0.1291	-0.1552	-0.15	-0.1931	-0.2388	-0.2017	-0.1498	-0.1715	-0.1873
St.Dev.	0.0399	0.0313	0.03	0.0282	0.0327	0.0365	0.0283	0.0463	0.0436	0.0414	0.0323	0.0357	0.0284

Table 4.4 continued

	Austria	Belgium	Germany	Denmark	Spain	Finland	France	Greece	Hungary	Ireland	Italy	Poland	Portugal
							Terms of trade volatility						
Mean	0.0124	0.011	0.0249	0.0155	0.0177	0.0456	0.023	0.0205	0.0134	0.0259	0.0834	0.0161	0.0233
Max	0.0313	0.0168	0.0308	0.0241	0.0295	0.0636	0.0288	0.031	0.0205	0.0425	0.1323	0.0258	0.0327
Min	0.0048	0.0059	0.0171	0.0112	0.0102	0.023	0.0164	0.0113	0.0045	0.0105	0.0391	0.0081	0.015
St.Dev.	0.0089	0.0035	0.0043	0.0042	0.006	0.0138	0.0053	0.0047	0.0055	0.0101	0.0319	0.0075	0.0061
							Local financials						
Mean	0.0002	-0.0012	-0.0001	0.0003	-0.001	0.0023	-0.0004	-0.0059	0.0008	-0.0072	-0.0021	0.0012	-0.0037
Max	0.1385	0.1732	0.1105	0.1588	0.1673	0.1074	0.1439	0.3409	0.2585	0.6683	0.1372	0.2033	0.273
Min	-0.2187	-0.2128	-0.1618	-0.236	-0.1579	-0.1619	-0.1556	-0.255	-0.3355	-0.7454	-0.1466	-0.2489	-0.1825
St.Dev.	0.0401	0.0408	0.0326	0.036	0.0395	0.0342	0.043	0.0637	0.0598	0.0973	0.0414	0.0396	0.0464
							Domestic bank assets						
Mean	0.0044	0.0029	0.002	0.0071	0.0073	0.01	0.0057	0.006	0.0068	0.0039	0.006	0.0109	0.0043
Max	0.0798	0.0481	0.1008	0.0963	0.0822	0.1062	0.0609	0.0674	0.0558	0.0552	0.0832	0.0684	0.0426
Min	-0.0387	-0.0707	-0.0269	-0.1163	-0.0209	-0.0802	-0.0439	-0.119	-0.0687	-0.0716	-0.0333	-0.0548	-0.0217
St.Dev.	0.0131	0.0215	0.0139	0.0381	0.0126	0.0314	0.0188	0.0195	0.0209	0.0211	0.0144	0.0246	0.011

Comprehensive sovereign credit ratings (CCR). Sovereign credit ratings reported by credit rating agencies (CRAs) reflect how likely it is that a country will default on its liabilities. Although these rating agencies have to be prudent in up- or down-grading a country based on new information and therefore the ratings sometimes lag behind market views, sovereign rating changes and outlook guidance are well-known to be related to CDS spreads and government bond yields (Afonso et al., 2011, Ismailescu and Kazemi, 2010). Hence, we use a comprehensive credit rating score (CCR) as in Gande and Parsley (2005) and Remolona et al. (2008b), where both sovereign credit ratings and outlooks/watches are converted to a numerical score, with 20 as the maximum score and 0 representing default, averaged over the three main CRAs (S&P, Moody's and Fitch).

Debt-to-GDP ratio. The value of a country's outstanding debts relative to the size of its economy affects the ability of that country to repay these liabilities in the long term. In the long run, these liabilities have to be repaid or rolled over, so the higher the level of debt compared to the size of the economy, the larger the risk that a country cannot fulfil its debt requirements in time.

Terms of trade volatility. A country's terms of trade affects its ability to repay its debt in the future. However, as Hilscher and Nosbusch (2010) highlight, it is mainly the volatility of the terms of trade that matters, as it shows whether any (adverse) shocks may occur to reduce either a country's ability or willingness to repay its debts. Higher terms of trade volatility are therefore likely to increase the probability of default.

Local stock market return volatility. Higher stock market volatility indicates higher (financial market) uncertainty and therefore increases the probability of default. It also partly covers other relevant forms of uncertainty that are hard to measure and quantify, such as political uncertainty.

Local stock market returns. The stock market is generally seen as a good representation and prediction of the overall state of the economy. Positive returns indicate a prosperous economy and thus a greater ability for sovereign obligors to repay debts, and as such stock market returns are expected to have a negative impact on the probability of sovereign default.

Change in domestic bank assets. The effect of growth of domestic bank assets is not straightforward. Before the crisis, a growing domestic banking sector was considered a good thing. A positive change in domestic bank assets was a sign of prosperous growth, and therefore this decreases a country's probability of default. However, during the crisis it became strikingly apparent that in bad times a large banking sector could transfer greater risks to the public sector. If banks in trouble need to be bailed out by governments, this puts a lot of pressure on the government's ability to pay for its liabilities and therefore increases its probability of default. We therefore expect a negative effect of changes in domestic bank assets on the probability of default before the start of the recent crisis period, and a positive effect thereafter.

Local financial index. Returns of the local financial index give a good representation of the state of the local financial sector. The reasons that the health of the financial sector matters for a country's ability to repay its debt(s) are similar to the ones mentioned for stock returns and domestic bank assets. On the one hand, it's an indication of the growth and state of the economy. On the other hand, a growing financial sector could cause problems for countries when they need to support them in times of (financial) turmoil.

Further details on these variables and descriptive statistics can be found in Tables 4.3 and 4.4 respectively. Note that we are obtaining fundamentals based default spreads, and therefore do not include measures for global risk aversion, suggested by Ang and Longstaff (2013), Fender et al. (2012) and Longstaff et al. (2011), at this stage of our analysis. We do however, control for global risk aversion in our subsequent estimation of the heterogeneous agent model. We also do not incorporate CDS spreads of other countries. An implication hereof is that we cannot attribute the difference between the fundamental and market spread soley to market speculation based on momentum trading activities. It is more likely to be a combination of a time-varying risk premium, omitted risks such as counterparty risk and contagion, as well as speculation. By estimating the model we can show that part of it is indeed caused by momentum. The first step of our analysis is to regress the implied hazard rates on the factors that affect the probability of default of a country and to predict fitted hazard rates based on that regression. We do this by estimating a panel regression with fixed effects. Because the dependent variable $h_{i,t}$ is a probability bounded between 0 and 1, we perform a logit transformation before regressing it on the explanatory variables:

$$logit(h_{i,t}) = log\left(\frac{h_{i,t}}{1-h_{i,t}}\right) = a_i + XB + \varepsilon_{t,i} \qquad (4.7)$$

Here the matrix X contains all country specific explanatory variables as mentioned above, as well as those variables that interact with a crisis dummy, which takes on a value of 0 up until the Lehman collapse on 15 September 2008 and 1 thereafter.[30] $h_{i,t}$ is the implied hazard rate for country i at time t. $a_{i,t}$ is a constant capturing country differences (country fixed effects), and B is a vector of coefficients.

4.4.3 Panel regression

The first step of our analysis is to regress the implied hazard rates on the factors that affect the probability of default of a country and predict fitted hazard rates based on the regression. We do this by estimating a panel regression with fixed country effects.

The results of estimating equation (4.7) are displayed in Table 4.5. We ran two different specifications of this regression, with seven and six explanatory variables respectively that are also interacted with a crisis dummy that assumes a value of 1 in all the weeks following the Lehman collapse on 15 September 2008 and zero otherwise. Under specification (A) in column two, out of seven explanatory variables, six have a significant impact on the risk-neutral probability of default. The signs are as expected. The comprehensive credit rating (CCR) score has a significantly negative impact on hazard rates, meaning that higher credit rating scores lower the probability of default. Interestingly, the effect of credit ratings is dampened during the crisis period. This is in line with the deteriorating faith of investors in credit rating agencies after they collectively failed to accurately rate securitized products and banks before the crisis. As expected, both an increase in debt-to-GDP ratio and an increase in terms of trade volatility increase a country's probability of default, and this effect becomes stronger during the crisis in case of the debt-to-GDP ratio. Stock market return volatility also increases a country's probability of default, but its impact is lower during the crisis, therefore the negative sign for this variable is in line with our expectations. However, because of the

[30] While the European Debt Crisis started at the end of 2009, we define our extended period of global debt market turmoil (i.e. crisis period) from Lehman Brother's collapse in 2008 as a large part of the stress in European debt markets emanated from the banking sector's exposures to U.S. mortgage backed securities. This has consequently increased sovereign credit risk as large public sector bailouts have ensued in some European countries.

positive sign for its interaction with the crisis dummy and the size of the coefficient being almost the same as before the crisis, we can say that during the crisis sample, stock market returns had negligible effects on a European sovereign's probability of default. Consistent with our expectations, a growing domestic banking sector was considered a good thing before the crisis as confirmed by the significant negative relationship with default risk. However, after the Lehman collapse and events following, it becomes clear that a large banking sector can put a lot of pressure on an economy if banks systematically get in trouble. We therefore see a positive sign for changes in domestic bank assets during the crisis period: a larger banking sector increased sovereign credit risk.

Table 4.5: Results implied hazard rate estimation

	(A)		t-stat	(B)		t-stat
constant	-3.4344	***	-17.15	-3.4304	***	-17.14
CCR	-0.283	***	-35.77	-0.2832	***	-35.8
*crisis dummy	0.1646	***	62.87	0.1647	***	62.88
Debt-to-GDP	0.0057	***	4.79	0.0057	***	4.79
*crisis dummy	0.008	***	14.03	0.008	***	14.01
Stock market vol	121.7142	***	46.16	121.6711	***	46.16
*crisis dummy	-96.9312	***	-34.33	-96.8762	***	-34.32
Stock market returns	-2.767	***	-3.84	-2.1469	***	-6.09
*crisis dummy	2.8967	***	3.58	1.8175	***	4.3
Terms of trade vol	2.4719	***	3.77	2.4911	***	3.79
*crisis dummy	1.1531		1.29	1.1499		1.28
Domestic bank assets	-1.5357	***	-2.88	-1.5332	***	-2.88
*crisis dummy	2.6635	***	3.9	2.6588	***	3.89
Local financials	0.6166		0.99			
*crisis dummy	-1.0082		-1.5			
Adjusted R-sq (within)	0.90065			0.90063		

The implied hazard rate estimation of Equation 4.7 by means of a fixed effects panel data method. Specification (1) in column 2 uses all selected variables and specification (2) in column 4 drops 'local financial' as it is not significant for the full sample period. T-statistics are shown in grey in the third column. ***, **, and * denote $p<0.01$, $p<0.05$ and $p<0.1$ respectively.

To predict fitted hazard rates we ultimately dropped local financials index (locfin) as it was not significant for the full sample period. This led us to use specification (B) in column four of Table 4.5 for predicted hazard rates to obtain the estimates on fundamental default spreads.

4.4.4 Market versus fundamental spreads

In Figure 4.2 the market and fundamental spreads are plotted together. By first observation, it looks as if some of the spikes of the CDS spreads are driven by movements in the underlying fundamentals. However, there are large misalignments between the market and the fundamental default spreads, which suggests that either non-fundamental trading (such as momentum) or increasing global risk aversion (and thus a higher risk premium demanded for bearing volatility risk) may have played an important role. Some countries, such as Germany, Finland, and France, have a lower market spread than their fundamentals would predict until end of 2010. This might be explained by the increasing demand for these bonds and thereby decreasing bond yields and CDS spreads in these countries. The CDS spreads of periphery countries show that the countries cannot just be grouped together. The credit risk of some countries, such as Ireland, Portugal and Spain, has been heavily overpriced compared to their fundamentals in recent years. These countries have suffered from both deteriorating fundamentals as well as an overreaction to that. Investors seem to have been too pessimistic about the state of those economies and their ability to repay their liabilities. From 2011 onwards there is a clear downward trend in the sovereign CDS spreads of these countries and CDS spreads reverted to more reasonable levels, at least for Spain and Portugal. For other countries, such as Italy, credit risk was not priced high enough for most of the crisis period. This is a strong sign that for some of the countries the rising spreads are a result of deteriorating fundamentals rather than excessive pessimism or speculation. In 2011, when most countries entered a more tranquil state, investors finally started to pick up on Italy's true credit risk and the market spread even overshot the fundamental levels until mid 2012, when the CDS spread dropped below its fundamental default spread again.

4.5 Model

Following the literature on heterogeneous agent models (for overview articles, see Hommes 2006; Chiarella et al. 2009a and Lux 2009), we develop a model for the pricing of CDS spreads based on heterogeneous expectations. Traditionally two types of agents are modelled, fundamentalists and chartists (labeled as momentum investors in this chapter). The assumption of two types of agents is mainly for convenience of discussion and this approach has been widely used in the heterogeneous agent model literature. As it would be difficult (and perhaps unrealistic) to identify whether an investor is a fundamentalist or a momentum investor , it is more likely that the expectation of an investor is a weighted average of beliefs on market fundamentals and momentum. In aggregation, the expectation of the market becomes a weighted average of the two beliefs. The weighting on the two components in market aggregate belief can be constant or time-varying, depending on the relative performance of the two beliefs.

The heterogeneous agent paradigm can be merged with more traditional credit pricing theories as follows. Fundamental expectations of future sovereign CDS spread movements are based on the state of the country's fundamentals and the ability of the market to price this. The fundamental rule therefore depends on the deviation between the market spread and the fundamental default spread.

Momentum expectations are formed based on the belief of persistency in trends (or trend reversals) in credit risk. That is, the momentum rule dictates extrapolation of past movements of CDS spreads into the future in order to form expectations about future CDS spread movements. This can be explained in different ways. It might be considered a form of naïve expectations, a decision for a costless rule, herding behavior, or a result of believing that the market generally underreacts (overreacts) to news, causing positive (negative) serial correlation and momentum (or contrarian) behavior (Barberis et al., 1998).

On top of these fundamental and momentum expectations, CDS spreads are driven by an extra premium, often referred to as the 'credit risk premium'. The credit risk premium depends on the time-varying willingness of investors to be exposed to the variability in CDS spreads and thus the price they require to bear the volatility risk in sovereign CDS markets[31]. In other words, the credit risk premium captures investors' average risk appetite.

The expectation of each investor is a weighted average of fundamental and momentum expectations. Investors are boundedly rational in the sense that they evaluate both expectation formation rules each period based on their past performance and attach more weight to a rule if it sufficiently outperforms the other rule. This means that the weights of each investors to the two expectations can be different from period to period. In aggregation, the weighting mechanism of the market follows the discrete choice model of Brock and Hommes (1997, 1998). It defines the probabilities of the two beliefs in market aggregation, which makes the changing weights of the two types of agents in the market a smooth rather than a random, process. When there are clear trends in CDS spreads, investors gradually assign more weight to the momentum expectation. Because expectations are self-fulfilling, this amplifies the momentum effect. An external shock might raise awareness about the importance of market fundamentals and might reverse investors' beliefs. Note that these dynamics can lead to both under- and overvaluation of sovereign credit risk.

To summarize, changes, ΔCDS_{t+1} in CDS spreads between period t and $t+1$ are driven by changes in credit risk premium, ΔRP_t, and a weighted average of the (net) fundamental and momentum demands D_t^m and D_t^f, respectively,:

$$\Delta CDS_{t+1} = \Delta RP_t + W_t\, D_t^m + (1 - W_t)\, D_t^f \tag{4.8}$$

Here, W_t is the market weight assigned to momentum expectations.

We now focus on the momentum and fundamental demand functions. The momentum demand D_t^m for CDS contracts in period t can be represented in the following way:

$$D_t^m = a^m(E_t^m[CDS_{t+1}] - CDS_t) \tag{4.9}$$

which is related to the expected change in the price of CDS contracts in the following period through a^m.

[31] An anonymous referee rightfully referred to this as "the price of fear and greed".

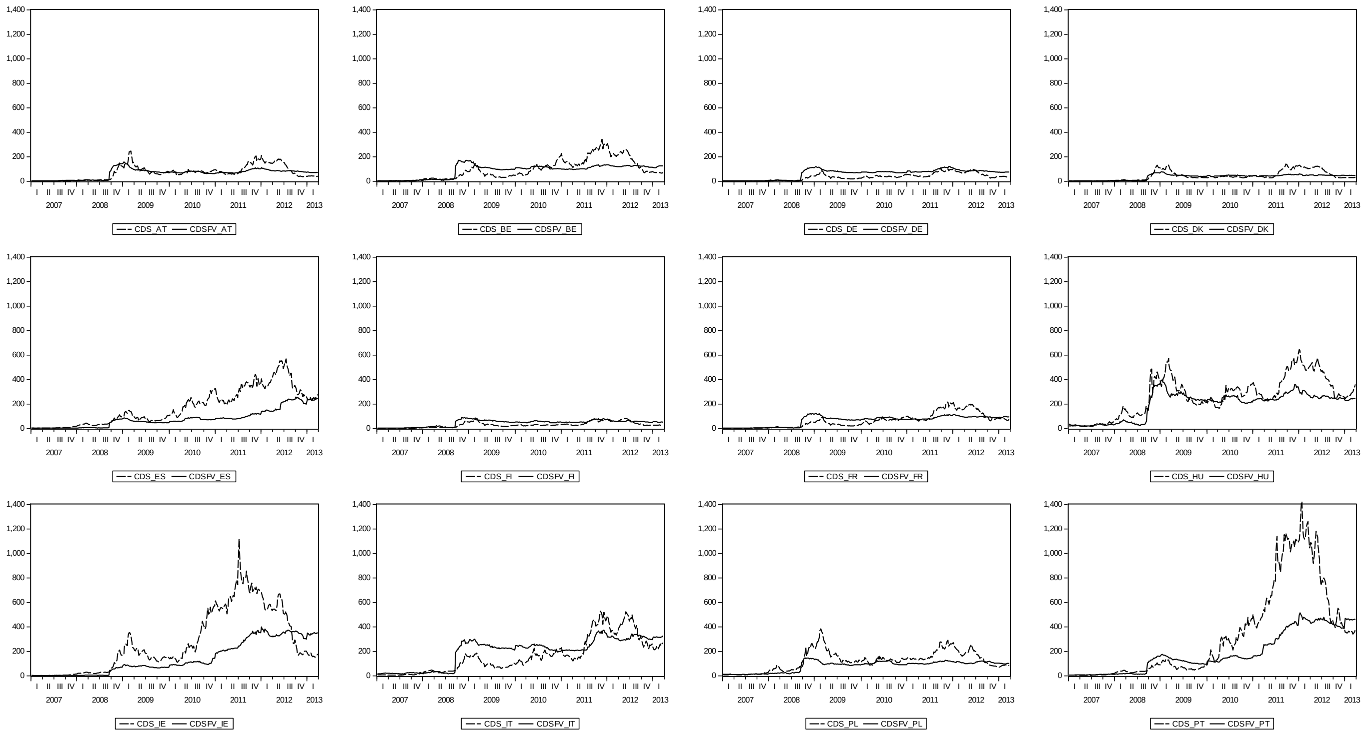

Figure 4.2 The sovereign CDS spreads and fundamental spreads for all countries in our sample ex Greece. Note that the scaling of the graphs is equal to facilitate comparison.

The demand is positively related to the expected price,$E_t^m[CDS_{t+1}]$, which depends on the current price CDS_t and a price trend over the past k periods CDS_{t-k}:

$$E_t^m[CDS_{t+1}] = CDS_t + \beta_m(CDS_t - CDS_{t-k}) \tag{4.10}$$

A positive (negative) coefficient of β_m is expected for momentum (reversion). The expectation is formed by extrapolating past movements of CDS spreads in the future.. As outlined before, there are several explanations for such behavior, such as herding or a belief in market underreaction (overreaction) to news. The momentum trading rule is of the same form as found for individual forecasting behaviour in laboratory learning-to-forecast experiments in Hommes et al. (2005) and Heemeijer et al. (2009).

Like the momentum demand, the fundamental demand is a positive function of the expected future price change:

$$D_t^f = a^f(E_t^f[CDS_{t+1}] - CDS_t) \tag{4.11}$$

However, the expectation of the future price $E_t^f[CDS_{t+1}]$ follows

$$E_t^f[CDS_{t+1}] = CDS_t + \beta_f(\overline{CDS_t} - CDS_t) \tag{4.12}$$

Here $\overline{CDS_t}$ is the fundamental default spread based on the estimated risk-neutral probability of default as in Section 3. Equation (4.10) shows that if the current CDS spread CDS_t deviates from the fundamental default spread, the future CDS spread is expected to move towards the fundamental default spread in the next period. We therefore expect a positive sign for β_f.

The weights of the fundamental and momentum components in market belief can be either constant or time-varying. As we indicated previously, the time-varying weights are modelled and interpreted by the following switching mechanism Following Brock and Hommes (1997, 1998), the functional form of the switching is a multinomial logit rule. The population weight in the market depends on the relative forecasting accuracy π_t^h (for h=m, f) of the respective forecasting rules:

$$W_t = \left[1 + exp\left(\gamma\left[\frac{\pi_t^m - \pi_t^f}{\pi_t^m + \pi_t^f}\right]\right)\right]^{-1} \qquad (4.13)$$

where W_t is the fraction of the momentum component in the market (and thus $[1 - W_t]$ is the fraction of the fundamental component in the market). The forecasting error is measured as the mean squared error (MSE) of each rule over the past J periods:

$$\pi_t^m = \sum_{j=1}^{J}[(E_{t-j}^m[CDS_{t-j+1}] - CDS_{t-j}) - \Delta CDS_{t-j+1}]^2 \qquad (4.14)$$

$$\pi_t^f = \sum_{j=1}^{J}[(E_{t-j}^f[CDS_{t-j+1}] - CDS_{t-j}) - \Delta CDS_{t-j+1}]^2 \qquad (4.15)$$

Following Ter Ellen and Zwinkels (2010), equation (4.11) differs slightly from the weighting mechanism originally proposed by Brock and Hommes (1997). Instead of using the absolute difference in forecasting accuracy of the two rules $\pi_t^m - \pi_t^f$, we calculate weights by using the relative forecasting (in)accuracy ($\frac{\pi_t^m - \pi_t^f}{\pi_t^m + \pi_t^f}$). Ter Ellen and Zwinkels (2010) argue that this method has the advantage~~s~~ of ease of estimation and comparability between different markets, which are useful in the current study to compare the results for the different European countries. The coefficient γ is called the intensity of choice and represents the investors' speed of switching[32]. If $\gamma = 0$, investors do not adapt the importance given to the two rules and $W_t = 0.5$. The other extreme is when $\gamma = \infty$ where investors are perfectly adaptive and immediately adjust all weight to the rule with the smallest forecast error. A small positive γ can be an indication of status quo bias, introduced by Kahneman et al. (1982). If investors suffer from this bias, they are reluctant to change their status quo belief, which results in slower updating of beliefs.

On top of these dynamics, CDS spreads are driven by an extra premium, often referred to as the 'credit risk premium'. As described earlier, the credit risk premium depends on the time-varying level of (global) risk aversion. Risk aversion is not directly measurable, but can be

[32] Or, in essence, the flexibility of an investor to change weights on the two respective trading rules.

proxied by the variance risk premium, the difference between option implied volatility and realized volatility[33]:

$$\Delta RP_t = \beta_{rp} \Delta VRP_t \tag{4.16}$$

Integrating equations (4.9)-(4.16) above to equation (4.8) and rewriting gives us the following set of equations to be estimated:

$$CDS_{t+1} - CDS_t = a + \beta_{rp}\Delta VRP_t + W_t(\beta_c(CDS_t - CDS_{t-k}))$$
$$+(1 - W_t)\big(\beta_f(\overline{CDS_t} - CDS_t)\big) + \varepsilon_t \tag{4.17a}$$

$$W_t = \left[1 + exp\left(\gamma\left[\frac{\pi_t^C - \pi_t^F}{\pi_t^C + \pi_t^F}\right]\right)\right]^{-1} \tag{4.17b}$$

$$\pi_t^C = \sum_{m=1}^{M} [(\beta_c(CDS_{t-m} - CDS_{t-k-m})) - \Delta CDS_{t-m+1}]^2 \tag{4.17c}$$

$$\pi_t^F = \sum_{m=1}^{M} [\big(\beta_f(\overline{CDS_{t-m}} - CDS_{t-m})\big) - \Delta CDS_{t-m+1}]^2 \tag{4.17d}$$

A constant a is included for estimation purposes, but theoretically it is expected to be zero. We estimate the model using quasi-maximum likelihood. To illustrate the explanatory power, we set the lag for momentum expectation at $k = 1$ and the lag for switching at $J = 4$.[34]

4.6 Results

We estimate the model with weights for both groups fixed to $W_t = 0.5$, for which results are shown in Section 6.1, and with time-varying weights as specified in equation (4.17) in Section 6.2. This allows us to evaluate whether dynamic switching between a momentum and fundamental strategy has had an additional impact on European sovereign CDS spreads.

[33] We followed the VRP calculation of Bekaert and Hoerova (2013) based on the S&P 500 index in order to account for the influence of global risk aversion (specifically the risk premium demanded for bearing volatility risk) in driving sovereign CDS spread movements.

[34] The price trend can be calculated by the lagged price, which is the simplest case or a weighted moving average with finite or infinite memory more generally, see Chiarella and He (2003a) and He and Li (2007). A Similar calculation applies to the forecasting error. To simplify the estimation, we use the lagged price of the previous week as the price trend and the last four weeks to calculate the forecasting error in this paper. Note that our results are robust to specifications for $k = 1$ to $k = 4$ and for $J = 1$ to $J = 4$. Results are available upon request.

We focus our analysis on the post-crisis period only from 2007 to 2013 as there was very little spread variation for European sovereign prior to this.[35]

4.6.1 Equal weights

Table 4.6 shows the results from estimating Equation (4.17) with fixed equal weights for the weighted fundamental and momentum expectations in sovereign CDS markets over the '(post-)crisis period' from 2007-2013. In this sub-sample period, CDS spreads are much more volatile and thus can be better explained by our model than in the pre-crisis sample. After controlling for the credit risk premium, we can see that in all thirteen countries, investors in each country extrapolate past trends in CDS spreads. The coefficients are all positive and significant, meaning momentum trading takes place. If there was a positive (negative) trend in the previous period, agents expect this trend to continue into the next period. Note that the coefficients are all between 0 and 1, so for none of the countries momentum expectations are 'explosive'. It is interesting to note that the range for the size of the momentum coefficients is roughly between 0.3 and 0.6, which is aligned with the laboratory-based learning-to-forecast experimental results in Hommes et al. (2005) and Heemeijer et al. (2009). In the 2-period ahead forecasting experiments in Hommes et al. (2005) the momentum or trend-extrapolating coefficients range from 0.4 to 1.3, while in the one-period ahead forecasting experiments of Heemeijer et al. (2009) (based on a similar price adjustment rule as Eq. (4.9) in the current chapter) the coefficients range from about 0.3 to 1.

[35] The 2004-2007 sub-sample results are available upon request.

Table 4.6: Results heterogeneity (equal weights for momentum and fundamentals)

	Const.		z-score	Mom.		z-score	Fund.		z-score	VRP		z-score	loglik
Austria	0.0035		0.64	0.5708	***	8.02	0.1027	***	4.48	0.1542	***	7.18	320.74
Belgium	0.006		1.13	0.4642	***	6.46	0.0401	***	2.66	0.1366	***	6.34	332.47
Germany	-0.01		-1.3	0.5209	***	8.29	0.064	***	3.27	0.1541	***	6.85	327.48
Denmark	0.0072		1.44	0.5885	***	7.7	0.0461	**	2.17	0.1451	***	7.76	339.38
Spain	0.0176	**	2.13	0.2936	***	3.34	0.0147		0.78	0.1264	***	7.45	346.54
Finland	-0.0142		-1.64	0.5062	***	7.42	0.0778	***	3.26	0.1323	***	7.63	354.01
France	0.005		0.93	0.4608	***	6.66	0.0492	***	3.05	0.1492	***	7.64	341.65
Greece	0.0212	***	3.33	0.6011	***	6.29	-0.004		-0.24	0.1052	***	3.94	243.09
Hungary	0.0119	**	1.96	0.4399	***	7.97	0.0383		1.54	0.1944	***	12.15	354.49
Ireland	0.0121		1.51	0.5555	***	6.73	0.0069		0.42	0.1225	***	6.79	338.68
Italy	0.0038		0.62	0.3904	***	4.95	0.0264		1.44	0.1651	***	8.83	346.56
Poland	0.0162	**	2.17	0.4144	***	5.66	0.0654	***	2.58	0.2028	***	11.51	334.73
Portugal	0.0131	***	2.51	0.4644	***	5.36	0.0233		1.53	0.1289	***	7.53	331.3

Estimates of the chartists and fundamentalists in Equation 4.16 with equal weights using maximum likelihood estimation (MLE). Z-scores are shown in grey in the third column. ***, **, and * denote p<0.01, p<0.05 and p<0.1 respectively.

Table 4.7: Results heterogeneity (time-varying weights for momentum and fundamentals)

	Const.		z-score	Mom.		z-score	Fund.		z-score	VRP		z-score	Sw. int.		z-score	loglik	2dLL	
Austria	0.005		0.95	0.3818	***	5.21	0.2198	***	9.02	0.1485	***	7.32	2.8423	***	3.7	331.18	20.89	***
Belgium	0.0053		1.03	0.5674	***	8.37	0.0262	***	3.18	0.1355	***	6.62	-6.841	***	-2.54	336.23	7.52	***
Germany	-0.0069		-1.06	0.291	***	3.94	0.1017	***	5	0.1524	***	6.8	3.4206	**	2.14	328.72	2.47	
Denmark	0.0069		1.39	0.5421	***	6.1	0.0565	**	2.17	0.1438	***	7.46	0.9137		0.57	339.51	0.25	
Spain	0.0262	***	3.06	0.1943	***	2.63	0.0754	**	2.04	0.1203	***	6.98	3.1591	*	1.71	348.25	3.41	*
Finland	-0.0165	**	-1.97	0.3484	***	4.85	0.1349	***	3.97	0.1357	***	8.24	1.5894	***	2.64	355.78	3.54	*
France	0.0041		0.79	0.2731	***	3.7	0.1113	***	5.73	0.1458	***	7.43	3.582	***	2.43	345.42	7.53	***
Greece	0.0207	***	3.25	0.6282	***	5.93	0.001		0.06	0.1055	***	3.96	-0.7389		-0.43	243.15	0.12	
Hungary	0.0098	*	1.72	0.5275	***	10.06	0.0197		1.48	0.1969	***	12.52	-4.4319	***	-2.71	356.44	3.9	**
Ireland	0.0094		1.47	0.6536	***	9.33	-0.0012		-0.15	0.1256	***	6.85	-6.7803	*	-1.88	343.18	9	***
Italy	0.0013		0.23	0.2702	***	3.5	0.0839	***	4.41	0.1609	***	8.56	5.6586		1.54	350.41	7.7	***
Poland	0.0218	***	3.18	0.3024	***	5.06	0.2392	***	4.07	0.1917	***	10.6	2.7074	***	4.47	336.75	4.04	**
Portugal	0.013	***	2.51	0.5527	***	6.04	0.014		1.32	0.134	***	7.98	-3.7198	*	-1.76	332.52	2.44	

The estimates of momentum and fundamentals 2007-2013 (time-varying weights). Z-scores are shown in grey. ***, **, and * denote p<0.01, p<0.05 and p<0.1 respectively.

Table 4.8: Descriptive statistics of the estimated weights

	Austria	Belgium	Germany	Denmark	Spain	Finland	France	Greece	Hungary	Ireland	Italy	Poland	Portugal
Mean	0.5711	0.5083	0.6495	0.5101	0.6648	0.5948	0.6151	0.4915	0.5035	0.5569	0.6308	0.6911	0.5109
Max	0.9448	0.9959	0.9678	0.7138	0.9563	0.8298	0.9725	0.6615	0.9754	0.9986	0.996	0.9355	0.9262
Min	0.0582	0.0016	0.0944	0.3157	0.0657	0.1897	0.0473	0.3491	0.0604	0.0038	0.0073	0.1117	0.0616
St.Dev.	0.2495	0.2747	0.2391	0.07	0.2129	0.1609	0.2534	0.0522	0.2329	0.2986	0.3035	0.2163	0.1996
Skew	0.0583	-0.1328	-0.4414	0.275	-0.6109	-0.3847	-0.1442	-0.2185	-0.0653	-0.3029	-0.3195	-0.7986	-0.2057
Kurt	1.6862	1.8863	1.9338	3.0947	2.4706	2.2096	1.7795	3.1675	1.9513	1.7415	1.704	2.3763	2.3414
Gamma	2.8423	-6.841	3.4206	0.9137	3.1591	1.5894	3.582	-0.7389	-4.4319	-6.7803	5.6586	2.7074	-3.7198

The descriptive statistics for the weights series obtained from estimating Equation (16). Note that the weights displayed represent the proportion of chartists in the market. The proportion of fundamentalists can be obtained by subtracting the chartist weight from one.

For seven out of thirteen countries, investors rely on the country's fundamentals. The positive sign for the fundamental component is consistent with the model assumption, indicating that when there is a misalignment between the market spread and the fundamental default spread agents follow a fundamental strategy and expect the spread to revert back to its fundamental spread. In this way they act as a stabilizing force in the market.[36] We can estimate the speed of reversion, in number of weeks, by calculating the ratio of one over the coefficient. If the beta coefficient for fundamentalists equals one, they expect the full misalignment to be reversed in the coming week. Strikingly, we reveal that the five countries without any significant presence of stabilizing fundamentalists are the peripheral countries that were in most trouble during the recent European sovereign debt crisis: Greece, Italy, Ireland, Portugal and Spain (with the sixth country Hungary as an exception). This suggests that the more extreme and volatile CDS spreads in these countries are attributable to momentum trading behavior rather than bad fundamentals.

4.6.2 Time-varying impact

The results of estimating equation (4.17) when investors change their weights to the two demand components based on the relative forecasting accuracy can be found in Table 4.7. The coefficients of the momentum component of all sovereign CDS markets are significant, suggesting momentum behavior in all the CDS markets. Whereas we would expect to see the largest momentum trading to occur in the peripheral countries, as it is sometimes claimed that they are most subjected to speculative attacks, this is not a pattern we can detect. Although the coefficients have changed slightly compared to the fixed-weights model, they are still well below one. In other words, we find no evidence that momentum trading in the peripheral or any other European sovereign CDS markets caused explosive CDS spread movements by chasing trends.

In recent laboratory experiments, Hommes (2011) and Anufriev and Hommes (2012) fit switching models with trend-following versus adaptive expectations (similar to the fundamentalists in the current chapter). Our results are remarkably consistent with the trend-following behavior observed in these laboratory experiments. The European CDS markets in

[36] The estimated fundamental coefficients are very small, less than 0.20, meaning that the fundamental expectations are close to naïve expectations.

2007-2013 have been characterized by clear phases of strong momentum that are well described by (temporary) coordination on simple momentum strategies.[37]

Nonetheless, fundamentals remained largely absent from the peripheral countries and momentum was the primary force driving their CDS movements during the crisis period. For the majority of (nine out of thirteen) markets investors are using a fundamental strategy in which they expect the market price misalignment from the fundamental default spread to decrease in the next period. Out of the five 'troubled' countries for which we could not see any impact of fundamental in the model with fixed weights, two countries, Spain and Italy, now show a positive and significant sign. In these markets, even though the market price of CDS contracts exceeds the levels warranted by fundamentals, there are some periodic movements towards the fundamental value.[38]

There are two channels that can lead to misaligned and more volatile CDS spreads. One is the strong dominance of momentum trading in the market, which is characterized by an insignificant switching intensity (γ), together with a significant coefficient for the momentum component and an insignificant coefficient for the fundamental component, which is clearly the case for Greece, Ireland, and Portugal. For Italy, the coefficient for the fundamental component is significant, but small; so with the insignificant switching coefficient we can also conclude that it is dominated by momentum trading. Another channel is the rational routes to randomness, developed in Brock and Hommes (1997, 1998) and characterized by significant switching among active strategies. This is illustrated by significant and positive coefficients of the fundamental and momentum components and the switching intensity. This is clearly the case for Spain, together with Austria, France, Hungary and Poland. On one hand, the fundamentals "work" in these countries; on the other hand, influenced by other EU countries, the speculative view taken on other countries has also spread to these countries. Overall, the

[37] We would like to thank the referee for pointing out the consistency between our empirical findings and laboratory experiment results, as well as the references. We have added the references and some related discussion in Sections 5 and 6.

[38] Based on the estimation, Belgium and Ireland have a significant negative switching intensity. Note that the estimated fundamental coefficients for the two countries are the smallest, 0.03 and 0.0023 respectively; while the estimated momentum coefficients, 0.58 and 0.65 respectively, are almost the largest among all countries. This implies that the fundamental expectation is reduced to a naïve expectation and the two markets are dominated by momentum trading. Hence, if the switching intensity were positive, the dominance of momentum trading would lead to explosive behavior. This could help to explain the negative switching intensity for the two countries. It may also be due to the limitation of the stylized model.

results reflect some realistic features on what has been occurring in these countries' sovereign credit markets.

To ascertain whether the model with time-varying weights performs better than the model with fixed weights, we compare the two models based on a likelihood ratio (LR) test. In such a way we can conclude whether the model with time-varying weights significantly outperforms the fixed weights model on the basis of their log likelihoods. The LR results can be found in the last column of Table 4.7[39]. The model with time-varying weights outperforms the fixed-weights model in seven out of thirteen cases. We can therefore say that in most EU countries investors have heterogeneous expectations and change the weights to different components over the time depending on the relative past performance of the respective components.

4.6.3 Time-varying weights

In order to gain more insight into the time-varying weights of momentum and fundamental expectations in European sovereign CDS markets, we include the descriptive statistics for the momentum weights in the market in Table 4.8. We can see that countries with a higher γ coefficient in equation (4.17) have a larger standard deviation in weights. They are more sensitive to changes in relative performance and therefore investors change their weights more often leading to more volatile weights.

Figure 4.3 illustrates the effect of a time-varying impact of momentum and fundamentals for four selected countries. It provides some intuition on the dynamics of the model. It displays the weight series for the momentum component over time, so a higher value corresponds to more momentum trading in the market and a lower value corresponds to more fundamental trading. It is observed that a higher weight of fundamentals generally coincides with the sovereign CDS spread moving closer to its fundamental default spread. When this trend is picked up by the momentum trading in the market, the weight of the momentum component increases. As momentum becomes relatively more dominant in the market, the CDS spread subsequently overshoots. This pattern repeats multiple times over the

[39] A likelihood ratio test involves comparing the differences in the log likelihood statistics between two nested models and evaluating whether this difference is significantly different from zero. The numbers in the 2dLL column are the result of multiplying the difference between the log likelihood of the static and the dynamic model.

full sample period studied and is most evident for the countries with a significant switching coefficient.

4.7 Conclusion

This chapter addresses the important question of whether the recent movements in European sovereign credit spreads are driven by weakened fundamentals or momentum trading behavior. In order to do this, a fundamental default spread is first calculated by means of regressing past hazard rates on a set of sovereign default determinants and using the resulting fitted values. Furthermore, to better explain the dynamics of sovereign CDS spread movements, a heterogeneous agent model with two key types of expectation formation rules and time-varying weights is estimated using market spreads and fundamentals-based spreads.

The estimation of our heterogeneous agent model reveals that in most European sovereign CDS markets both fundamental and momentum expectations played a role. In peripheral countries fundamental expectations were dominated by momentum throughout the crisis period contributing to the observed higher spreads. Momentum trading exerted a destabilizing effect on the market by prolonging price trends. In some cases, fundamental expectations pulled the market spreads back to their fundamental-based level, thereby stabilizing CDS spreads. The change in the market weights of these two expectations coincided with larger market movements and both movements towards and away from the fundamentals implied-spread. The model with time-varying weights is a significant improvement over the model with fixed weights.

To conclude, the recent movements in European CDS markets can be partly explained by deteriorating fundamentals for core countries strained by the obligation to support the troubled peripheral countries and a weakened Eurozone. However, momentum expectations, as well as switching between different these forecasting rules also played a significant role in explaining the sovereign CDS market dynamics. Based on our results we can conclude that for the five troubled peripheral countries, momentum trading played a much more dominant role in increasing their sovereign CDS spreads beyond the levels justified by weakening fundamentals.

The model proposed in this chapter is of course very stylized and we do not take into account potential spill-over effects between national CDS markets when investors trade across multiple markets. Flight to safety has been suggested as one of the reasons for the strong increase of CDS spreads in peripheral countries. Taking these effects into account, extending the model in a portfolio setting, and allowing cross-country / cross-market switching based on credit risk or fundamentals of other (regional) countries would be an interesting avenue for future work.

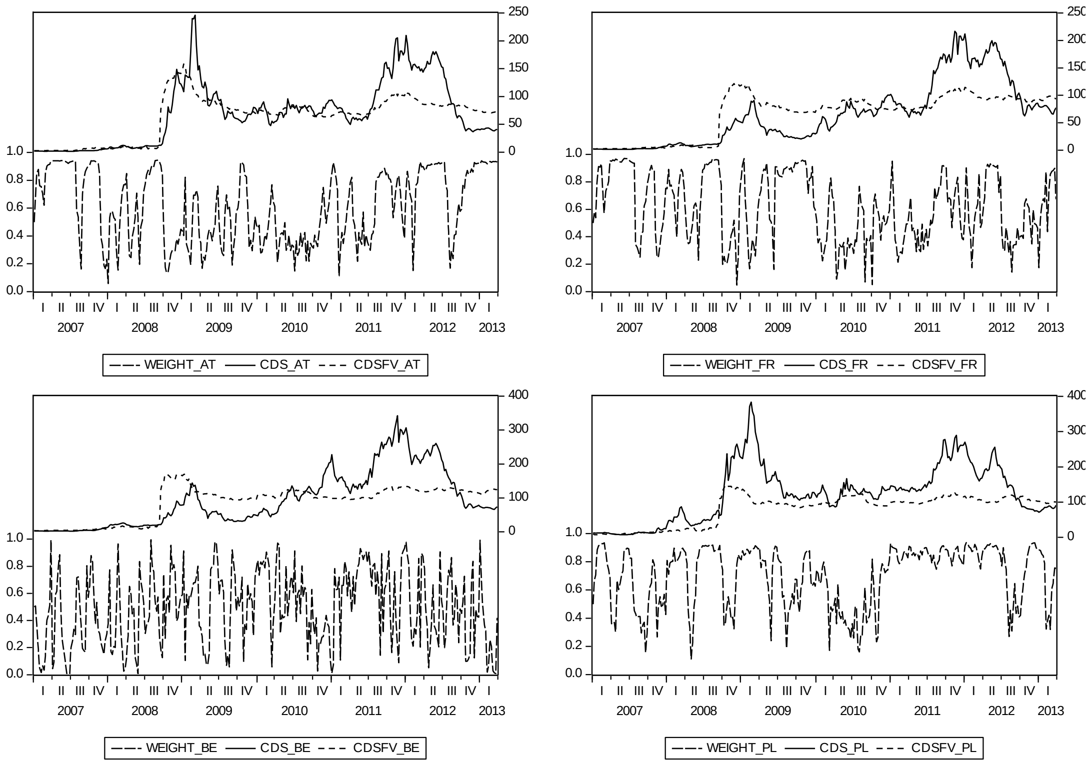

Figure 4.3 The sovereign CDS spreads, fundamental spreads and time-varying weights for four selected countries. For these countries the time-varying weights model outperforms the model with equal weights and both strategies have significant coefficients.

Agreeing on Disagreement:

5 Heterogeneity or uncertainty in the foreign exchange market?[40]

5.1 Introduction

In this chapter we study heterogeneity and uncertainty and their relation to risk in the foreign exchange market. The heterogeneous nature of agents in economic and financial markets is becoming increasingly embedded in the finance literature, often by taking into account the disagreement between different market participants (i.e. dispersion of beliefs). Support for such an approach comes from different sources. Fama and French (2007) conclude that disagreement matters for asset pricing if investors are risk averse. If informed traders were risk neutral, they would offset the positions of the uninformed traders and CAPM prices would sustain. Carlin et al. (2012) analyze the effects of disagreement in the market for mortgage backed securities (MBS) and find that disagreement (heterogeneity) is associated with higher expected returns and higher trading volume. They state that "[in this market] it is much more likely that disagreement among dealers is due to differences in their model choice, underlying assumptions, and interpretation of economic news". Giordani and Soderlind (2006) show that disagreement about the growth rate of consumption increases the equity premium in an Arrow-Debreu economy. Buraschi and Whelan (2012) focus on bond markets and show that bond risk premia and volatility of the term structure are affected by disagreement about macroeconomic fundamentals and future bond prices. Anderson et al. (2005) find that heterogeneity of beliefs matters for asset pricing, and that their proxy of disagreement about earnings is a risk factor affecting both equity returns and volatility.

[40] This chapter is based on "Ellen, ter S., W.F.C. Verschoor and R.C.J. Zwinkels (2015), Agreeing on Disagreement: heterogeneity or uncertainty in the foreign exchange market?, working paper."

Several authors have linked disagreement or dispersion in beliefs to foreign exchange markets and puzzles. Fisher (2006) proposes a model where the foreign exchange forward premium depends on the diversity of prior beliefs about a country's inflation process. Gourinchas and Tornell (2004) propose a solution for both the forward premium puzzle and the delayed overshooting puzzle based on investor's distorted beliefs about interest rates. Beber et al. (2010) show that disagreement about future currency returns has a large impact on currency risk premia.

Empirically, (analyst) disagreement has not only been used to measure heterogeneity. The measure is becoming increasingly popular to proxy for uncertainty as a part of risk that volatility alone does not cover[41]. Bomberger (1996) analyzes the relation between disagreement and uncertainty measured as the conditional variance of an individual forecast, and concludes that the two are strongly related. Likewise Giordani and Soderlind (2003) show that disagreement is a better proxy of inflation uncertainty than what previous literature has indicated. Various studies have found that uncertainty has an impact on the risk premium of assets. Anderson et al. (2009) link a disagreement factor, based on the weighted cross-sectional volatility of equity return forecasts, to equity premia. They find that this measure of uncertainty is more important in explaining the equity premium than volatility.

Despite the fact that the literature on dispersion of beliefs is already quite extensive, a solid conclusion about the different interpretation of disagreement has not been reached. This may be best captured by two papers from Anderson et al. (2005, 2009). In their 2005 paper, they argue, both theoretically and empirically, that heterogeneous beliefs matter for asset pricing. They first derive the pricing kernel under the assumption of agents with heterogeneous beliefs. In the empirical part of the paper, where heterogeneity of beliefs is measured by disagreement of earnings forecasts, the authors show that heterogeneity (earnings disagreement) is a priced risk factor in equity markets. In their 2009 paper, a similar result is established for disagreement being a priced risk factor. However, in this case disagreement is assumed to measure uncertainty and therefore the conclusion is that uncertainty is a priced

[41] In finance and economics, different definitions of risk and uncertainty are used. In some cases, uncertainty is the 'umbrella' term, capturing both risk (known unknowns) and ambiguity (unknown unknowns). In some cases risk is defined as the aggregate of known and unknown unknowns, but proxied by measures of known unknowns. In other papers, risk is the 'umbrella' term and composed out of volatility (known unknowns) and uncertainty (unknown unknowns). We follow the latter approach.

risk factor. Although there are many differences in the two approaches, of which the most important is perhaps the difference between disagreement of idiosyncratic earnings and aggregate corporate profits, the fact that a similar measure is used to measure heterogeneity and uncertainty respectively is characteristic for this measure[42].

Arguments for disagreement being a measure of heterogeneity or uncertainty are appealing for both interpretations. If there is high uncertainty about future exchange rate movements, distance between forecasts is large (i.e. agents heavily disagree about their point forecasts). However, the distance between forecasts may also be large because investors (prefer to) have different forecasting models, have information asymmetry, have limited attention, and/or are affected by other psychological traits.

In this chapter, we will analyze whether the time-variation in disagreement (dispersion of forecasts of future exchange rate movement) is mostly representative of time-variation in the heterogeneity of agents' beliefs, or rather of time-variation in uncertainty. To this end we utilize a standard VAR model to disentangle the direction of the relation between disagreement and volatility. In doing so, we build on the proposition that the relation between uncertainty and volatility is mostly contemporaneous (volatility is often even used as a measure or proxy for uncertainty), and the relation between heterogeneity and volatility runs from the former to the latter (more heterogeneity induces more noise trading, which leads to higher levels of volatility). We also look into the (possibly time-varying) relation between disagreement and volume and disagreement and liquidity, thereby building on the proposition that there should be a positive relation running from heterogeneity (uncertainty) to volume (illiquidity) and vice versa. The data we employ captures disagreement of future exchange rate movements for two major currency pairs, the EUR/USD and the USD/JPY. One of the main benefits of focusing our analysis on the foreign exchange market is that our results will not be affected by short sale constraints. This reason was also brought forward by Beber et al. (2010) for studying the foreign exchange market, and by Carlin et al. (2012) for studying the MBS market.

Our results suggest that the time-variation in disagreement measures time-variation in heterogeneity in tranquil times, but becomes a good measure of uncertainty during a period of

[42] A possible explanation for the case of Anderson et al. (2005, 2009), might be that idiosyncratic disagreement measures heterogeneity, and aggregate disagreement measures uncertainty.

turmoil. After having established this, we analyze whether disagreement has added value over realized volatility when linking it to risk and risk premium. Malkiel (1982) states that "the best single risk proxy is not the traditional beta calculation but rather the dispersion of analysts' forecasts". Anderson et al. (2009) confirm this. We find that disagreement indeed has explanatory power for risk and risk premia beyond realized volatility, and that its impact is sometimes even larger than the impact of realized volatility. Moreover, we find that disagreement is only linked to our measure of total risk in times of turmoil, whereas realized volatility has a constant relation with total risk. This confirms our result that disagreement only measures uncertainty in periods of turmoil.

The remainder of the chapter is set up as follows. Section 2 describes the data and our hypotheses and results concerning whether time-variation in disagreement measures time-variation in heterogeneity or uncertainty. Section 3 assesses the added value of disagreement in explaining risk and risk premia. Section 4 summarizes the results and discusses implications for current and future research.

5.2 Heterogeneity and uncertainty

5.2.1 Data

The focus variable used for our analyses is disagreement between analysts, also referred to as dispersion of analyst forecasts. To be more precise, disagreement is the cross-sectional (across respondents) standard deviation of the analysts' 1, 3 and 12 months ahead forecasts. To measure disagreement, we use a dataset with monthly forecasts from financial analysts and investors gathered by Consensus Economics®. Consensus Economics is the world's leading international economic survey organization and their datasets are unique in terms of their long time span, large number of respondents, level of responding institutions, and the disaggregate level of forecasts. Forecasts are given every month for the future value of the dollar against the Euro and the Japanese yen 1, 3 and 12 months ahead. As previously mentioned, a main benefit of focusing our analysis on the foreign exchange market is that our results will not be affected by short sale constraints. Our survey sample runs from January 1999 to December 2009[43].

We use implied volatilities, and spot and forward exchange rates from Thomson Reuters (obtained through Datastream). Realized volatility is calculated as the sum of squared 15 minute returns over the past 30 days. Data on 15 minute prices is obtained from Reuters RTCE (Reuters Tick Capture Engine)[44]. Our high-frequency return sample runs from January 2001 to December 2009.

As Pastor and Stambaugh (2001) state, "liquidity is a broad and elusive concept that generally denotes the ability to trade large quantities quickly, at low costs, and without moving the price". Our liquidity measures relate to the trading at low costs (bid-ask spread) and trading without moving the price (high-low spread). High bid-ask spreads (computed as the difference between the ask and bid spread divided by the mid-spread) reflect high transaction costs and make it more expensive to trade. High-low spreads (log of the highest price of the day minus log of the lowest price of the day divided by the log of the number of trades) indicate the impact that trades have on prices, per unit of trade. In illiquid markets, trades have a larger impact on prices and we would therefore see larger high-low spreads. We obtain bid-ask spreads and high-low spreads from Reuters. Bid ask-spreads are averaged over the day and over the future month, following the Consensus forecast date. High-low spreads are converted to monthly frequency by taking the maximum 'high' and minimum 'low' over the day, averaging these over the future month following the Consensus forecast date, and dividing the resulting spreads by the trading volume of that month.

A direct measure of FX trading volume is difficult, if not impossible, to obtain as the foreign exchange market is decentralized. The RTCE data provides us with two different proxies for trade: number of trades (per 15 minutes) and ask-quote frequency (per 15 minutes). Hartmann (1999) uses reported Japanese FX broker volume to proxy for trading volume, and finds his results are robust to using Reuters FXFX quoting frequency ('tick count'). In an earlier paper, Hartmann (1998) shows that monthly Reuters ticks are strongly

[43] However, because the sample of our other data runs from 2001, we will use a sample from January 2001 until December 2009 for all our analyses.

[44] Most inter-dealer FX trading is executed on either Reuter's or EBS' platforms. Although EBS is the main trading platform for the EURUSD and USDJPY, a substantial amount of trading for these currency pairs takes place via Reuters..

correlated with monthly trading volumes (from Japanese FX brokers). However, there are a few disadvantages of using tick frequency. First of all, Hartmann (1998) found that the relationship between volume and ticks is unstable over time. Also, tick frequency is not the same as transaction frequency – there may not be trading at every quote. We therefore choose to use number of trades (also referred to as 'trade count' in the rest of the chapter) as our main proxy for trading volume. However, even transaction frequency has the disadvantage of not capturing the amounts at which is traded. In times of uncertainty and/or low liquidity, traders may decide to cut trades up in smaller portions, thereby lowering average trade size but keeping transaction frequency equal or perhaps even increasing their transaction frequency. We therefore obtain a second proxy for FX trading volume as a robustness check, FX futures volume (used by, among others, Frankel and Froot, 1990) from CME.

Finally, we also detrend and standardize some of the data to respectively deal with unit roots and for the ease of comparability. First of all, futures volume contains a unit root and is detrended using the Hodrick-Prescott (HP) filter (1997). More specifically, we use the filter to decompose our measure into a trend and a so-called cycle component. It is this cycle-component that is stationary and that we use for our analysis. Disagreement, realized volatility, implied volatility and our measures for FX trading volume and liquidity are standardized for the ease of comparability[45].

5.2.1.1 Descriptive statistics

Descriptive statistics for the variables of interest are shown in Table 5.1. We can see that the longer the horizon, the larger the disagreement is on future values of the exchange rates. We can further see that the market for EURUSD is larger than the market for USDJPY, both in terms of number of trades and number of futures contracts traded, and is more liquid, as seen by the lower bid-ask spreads and scaled high-low spreads. Note that the size of one EURUSD (USDJPY) futures contract is EUR 125,000 (JPY 12,500,000), whereas the average trade size in the interdealer market may be closer to USD 2 million.

[45] The variables are standardized as to having a mean of zero and a standard deviation of one.

Table 5.1: Descriptive statistics of main variables

		Mean	**Median**	**Maximum**	**Minimum**	**Std. Dev.**
			Disagreement			
EURUSD	1m	0.028	0.026	0.065	0.014	0.0096
	3m	0.0408	0.039	0.076	0.026	0.0115
	12m	0.0677	0.066	0.102	0.039	0.0142
USDJPY	1m	2.7533	2.7	5.7	1.7	0.6581
	3m	4.007	3.9	6.4	2.8	0.7527
	12m	6.8065	6.8	11.2	4.7	1.0866
			Volatility			
EURUSD	Realized volatility	3.5428	3.2713	10.5349	1.6513	1.4209
	Implied volatility	10.2005	9.8375	21.75	5.05	3.0202
USDJPY	Realized volatility	2.6856	2.486	8.286	0.4721	1.2804
	Implied volatility	10.6426	9.75	24	6.375	3.2644
			Volume			
EURUSD	Trade count	38025	39175	76470	6432	14975
	Futures	2477859	2758136	5989844	73167	1531210
USDJPY	Trade count	3229	2905	7119	1091	1425
	Futures	1260497	1042918	3726350	244616	884333
			Liquidity			
EURUSD	bid-ask (%)	0.0015	0.001	0.0099	0.0003	0.0017
	(high-low)/tc	2.94E-03	1.51E-03	2.53E-02	4.77E-04	3.85E-03
USDJPY	bid-ask (%)	0.0022	0.0022	0.0066	0.0005	0.001
	(high-low)/tc	4.35E-03	1.50E-03	9.68E-02	5.26E-04	1.11E-02

Descriptive statistics for disagreement (cross-sectional standard deviation of analysts' forecasts of the exchange rate 1, 3, and 12 months ahead), realized volatility (cumulative 5 minute squared returns over the past 30 days), and implied volatility (option implied volatilities for maturity of 1 month).

As mentioned in the previous section, there are various ways to proxy for volume and liquidity in foreign exchange markets. We therefore use two different proxies for each. In Table 5.2 we can see to what extent these variables are related, by analyzing their correlations. We can compare the measures along two dimensions; we can assess whether they are related within one market (EURUSD or USDJPY) or whether they are related across markets. Strikingly, the correlation between trade count and futures volume is very low: around 0.24 for the USDJPY market and close to zero for the EURUSD market. The number of trades across markets is also uncorrelated. This implies that the two volume proxies seem to measure completely different aspects of the true volume in these FX markets. If we turn to our liquidity measures, we even see the opposite pattern: the liquidity measures for EURUSD are correlated, but the correlation for USDJPY liquidity measures is close to zero.

Figure 5.1 gives a graphical representation of the HP filter decomposed measures of volume. Although futures volume shows a clear trend, once we filter out the trend it looks like a much more stable measure of volume.

5.2.2 Timing, volume, and liquidity

To investigate whether disagreement is mostly measuring uncertainty or heterogeneity, we make use of the timing of the disagreement-volatility relation[46]. As Frankel and Froot (1990) state in their seminal paper on heterogeneity in the foreign exchange market, more heterogeneity induces more noise trading, which leads to higher levels of volatility. Carlin et al. (2012) confirm this prediction for the MBS market. The relation between heterogeneity and volatility should therefore be running from heterogeneity to volatility.

Hypothesis 1a: If analyst disagreement measures heterogeneity, we should see a link running from disagreement to volatility.

The relation between uncertainty and volatility can be seen as a contemporaneous one – volatility is often even used as a measure or proxy for uncertainty. In times of high uncertainty, asset volatility is generally higher. Alternatively, financial market participants may become more uncertain about their point forecasts when volatility is high. In that case, the relation runs from volatility to uncertainty.

Hypothesis 1b: If analyst disagreement measures uncertainty, we should see a contemporaneous relation between disagreement and volatility

[46] At this point we should make clear that, going forward, when we talk about heterogeneity, we mean every type of heterogeneity that is not directly caused by uncertainty. For example, investors may be heterogeneous because they (prefer to) have different forecasting models, have heterogeneous information, have limited attention, and/or are affected by other psychological traits. When investors' heterogeneity is caused by uncertainty, we call this uncertainty.

Table 5.2: Correlation tables for volume and liquidity measures

	Liquidity measures		
	bid-ask (EURUSD)	**bid-ask (USDJPY)**	**high-low (EURUSD)**
bid-ask (EURUSD)	1.00		
bid-ask (USDJPY)	0.47	1.00	
high-low (EURUSD)	0.68	0.40	1.00
high-low (USDJPY)	-0.06	-0.04	0.24
	Raw volume measures		
	trade count (EURUSD)	**trade count (USDJPY)**	**futures cycle (EURUSD)**
trade count (EURUSD)	1.00		
trade count (USDJPY)	-0.04	1.00	
futures cycle (EURUSD)	-0.02	0.04	1.00
futures cycle (USDJPY)	0.11	0.24	0.47

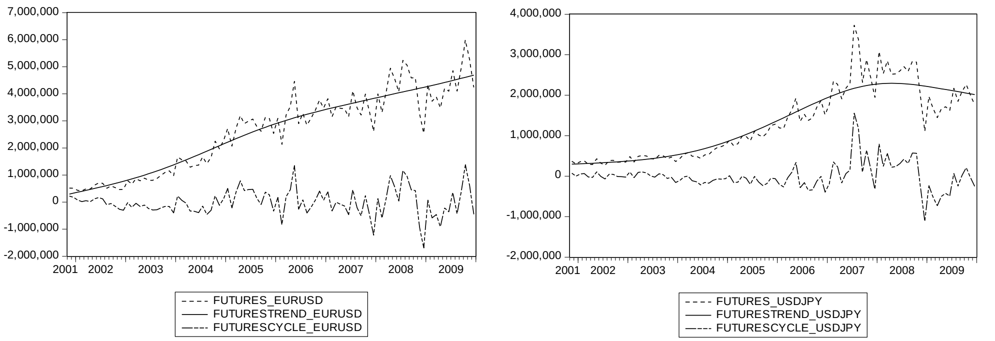

Figure 5.1. Graphical representation of applying the Hodrick-Prescott filter to obtain decomposed futures volume (blue line) in a trend (red line) and a cycle (green line) component.

Hypothesis 1c: If analyst disagreement measures uncertainty, we should see a link running from volatility to disagreement.

As stated above, more heterogeneity induces more noise trading, which leads to higher levels of volatility (Frankel and Froot, 1990). It is by now well established that the large volume of foreign exchange markets cannot be explained by international trade only (Frankel and Froot, 1990), and that heterogeneity of market participants is necessary for such large volumes. Unless disagreement is caused by uncertainty, it will lead to more trading. This positive relation between heterogeneous beliefs and volume is documented by, amongst others, Buraschi and Jiltsov (2006), Banerjee and Kremer (2010), and Buraschi and Whelan (2012). Lee and Swaminathan (2000) even use high trading volume as a proxy for differences of opinion. Carlin et al. (2012) find that higher disagreement in the MBS market (stemming from model choice and information interpretation) is followed by higher volume and higher volatility. Whereas heterogeneity has a positive effect on volume (and to some extent liquidity), uncertainty generally reduces volume and liquidity, as investors are more hesitant to update their portfolios (Buraschi and Whelan, 2012; de Castro and Chateauneuf, 2011). This is to some extent confirmed by Carlin et al. (2012), who find that volatility does not lead to higher trading volume. Therefore we can use volume as a distinguishing factor between uncertainty and heterogeneity.

Hypothesis 2: If analyst disagreement measures heterogeneity, we should see a positive relation between disagreement and volume.

Hypothesis 3a: If analyst disagreement measures uncertainty, we should see a negative relation between disagreement and liquidity.

Hypothesis 3b: If analyst disagreement measures heterogeneity, we should see a positive relation between disagreement and liquidity.

The relation between uncertainty and volume is not that straightforward. In times of high uncertainty investors may be hesitant to update their portfolios, resulting in lower trading volumes, or they may unwind some (risky) positions, leading to lower liquidity but larger trading volume. Testing hypothesis 2 will therefore give us some insight in whether disagreement measures heterogeneity or not, but will not give us much information on whether disagreement measures uncertainty. On the other hand, liquidity is expected to be higher when heterogeneity is higher (because of higher trading volume and more investors willing to take the other side of a position), but lower when uncertainty is higher. Testing hypotheses 3 a and b should therefore shed some more light on this distinction.

5.2.2.1 Timing tests

Periods of high uncertainty are associated with periods of high volatility. Hence, a contemporaneous relation between volatility and disagreement indicates uncertainty. This is measured in a simple OLS setup by

$$\psi_t = \alpha + \beta\sigma_t + \varepsilon_t \tag{5.1}$$

Here, ψ_t denotes disagreement measured as the cross-sectional standard deviation of survey forecasts, and σ_t denotes realized volatility measured from 15 minute square returns. The results of this regression are displayed in Table 5.3. We can see that there is a strong contemporaneous relation between volatility and disagreement. This relation is the strongest for the short horizon, where we use dispersion of the 1 month ahead forecasts, and for the EURUSD exchange rate. This is in line with hypothesis 2a, and thus indicative for disagreement measuring uncertainty. However, there may also be a relation running from disagreement to volatility.

Table 5.3: Results disagreement and realized volatility (OLS)

	1m				3m				12m			
	EUR USD		USD JPY		EUR USD		USD JPY		EUR USD		USD JPY	
constant	0.0207		0.0056		0.0409		-0.0536		0.0441		-0.1146	
	0.1844		0.0346		0.3158		-0.3221		0.2707		-0.6883	
realized volatility	0.7173	***	0.3049	***	0.6794	***	0.2795	**	0.4959	***	0.0604	
	10.3587		2.5550		10.1128		2.3071		3.1102		0.5331	
adj R2	0.5163		0.0755		0.4650		0.0670		0.2382		-0.0058	

Results from estimating Equation 5.1, the contemporaneous relation between disagreement and realized volatility. Note that the variables are standardized for ease of coefficient interpretation. T-statistics are displayed under the coefficients (shaded).

Heterogeneity induces more (noise) trade and therefore more volatility. Hence, if there is a relation running from disagreement to volatility, this is an indication that it may capture time-variation in heterogeneity. In case disagreement measures uncertainty, there should be a relation from volatility to disagreement. We estimate a VAR with two lags[47] to capture the possibly two-way relation between disagreement and volatility. We also perform Granger causality tests to investigate whether disagreement Granger causes volatility or vice versa.

$$\begin{bmatrix}\sigma_t^2\\ \psi_t^2\end{bmatrix} = \begin{bmatrix}\alpha_1\\ \alpha_2\end{bmatrix} + \begin{bmatrix}\beta_{1;11} & \beta_{1;12}\\ \beta_{1;21} & \beta_{1;22}\end{bmatrix}\begin{bmatrix}\sigma_{t-1}^2\\ \psi_{t-1}^2\end{bmatrix} + \cdots + \begin{bmatrix}\beta_{2;11} & \beta_{2;12}\\ \beta_{2;21} & \beta_{2;22}\end{bmatrix}\begin{bmatrix}\sigma_{t-i}^2\\ \psi_{t-i}^2\end{bmatrix} + \begin{bmatrix}\varepsilon_{1,t}\\ \varepsilon_{2,t}\end{bmatrix} \tag{5.2}$$

The results of this estimation are displayed in Table 5.4. There is no strong evidence for either hypothesis 1a or 1c. The results for USDJPY show there is no Granger causality from disagreement to volatility or the other way around, nor are there clear lead-lag relations. The results for EURUSD are not clear: for the short and medium forecast horizon, disagreement Granger causes volatility, favoring the heterogeneity hypothesis (1a). However, the exact opposite is the case for the long horizon where volatility Granger causes disagreement. We can therefore say that the VAR results are inconclusive.

5.2.2.2 Volume and liquidity tests

After having analyzed the timing of the disagreement-volatility relation, we now turn to analyzing the effect of disagreement on trading volume. We analyze this relation because the noise trading caused by heterogeneity of expectations should show up in trading volumes. We first look at the unconditional relation between disagreement and volume.

$$tvol_t = \alpha + \beta\psi_t + \varepsilon_t \tag{5.3}$$

[47] To be able to compare the results over forecast horizons and currencies, we imposed the same lag structure on all VARs. A lag of 2 was obtained by comparing the AIC over different lags and choosing the number of lags that had the highest AIC for most horizons over both currency pairs.

Table 5.4: Results disagreement and realized volatility (VAR)

	EURUSD				USDJPY			
	disagreement		volatility		disagreement		volatility	
	1 month							
disagreement(-1)	0.5104	***	0.4862	***	0.5686	***	0.0895	
	4.7672		4.5747		5.357		1.1217	
disagreement(-2)	0.2252	**	-0.3257	***	0.0267		-0.1604	**
	2.0993		-3.0591		0.2471		-1.974	
volatility(-1)	0.196	*	0.7714	***	-0.0613		0.4868	***
	1.9062		7.5587		-0.4536		4.7889	
volatility(-2)	-0.0329		-0.1045		0.1858		0.3628	***
	-0.3156		-1.0111		1.3699		3.5563	
adj R2	0.6988		0.7113		0.3646		0.6078	
Granger test	4.4396		21.1891		2.6167		3.8992	
p-val	0.3498		0.0003		0.6239		0.4198	
	3 months							
disagreement(-1)	0.7003	***	0.4505	***	0.7096	***	0.0458	
	6.4997		3.0346		6.6886		0.4585	
disagreement(-2)	0.1856	*	-0.2952	**	0.0376		-0.1278	
	1.7594		-2.031		0.3485		-1.2578	
volatility(-1)	0.1222		0.7723	***	0.0816		0.5003	***
	1.6079		7.3745		0.7555		4.9213	
volatility(-2)	-0.0531		-0.0918		0.0204		0.3481	***
	-0.6803		-0.8539		0.1872		3.3859	
adj R2	0.8294		0.6849		0.5591		0.5999	
Granger test	2.786		9.7467		1.8448		2.0333	
p-val	0.5942		0.0449		0.7643		0.7296	
	12 months							
disagreement(-1)	0.6866	***	0.2126		0.7614	***	0.0477	
	6.5635		1.3945		7.3646		0.3437	
disagreement(-2)	0.1239		-0.258	*	0.1014		-0.1374	
	1.2624		-1.8033		0.9681		-0.9769	
volatility(-1)	0.1654	***	0.8416	***	-0.0383		0.5003	***
	2.3286		8.1318		-0.5081		4.9436	
volatility(-2)	0.0507		-0.0418		0.1108		0.3301	***
	0.6581		-0.3727		1.4776		3.2769	
adj R2	0.8407		0.6635		0.7259		0.599	
Granger test	17.8704		3.361		3.0782		1.8166	
p-val	0.0013		0.4993		0.5448		0.7694	

Results from estimating Equation 5.2, a VAR model to study the lead-lag relations between disagreement and realized volatility. Note that the variables are standardized for ease of coefficient interpretation. T-statistics are displayed under the coefficients (shaded).

Here, ψ_t denotes disagreement, and $tvol_t$ denotes trading volume, where trading volume is either proxied by RTCE number of trades or detrended CME futures volume. Results of estimating Equation 5.3 by means of OLS can be found in Table 5.5. We can see that there is no unconditional contemporaneous relation between disagreement and trading volume for the EURUSD market, regardless of whether we use futures volume or number of trades as proxies for trading volume. However, the results for the USDJPY market show a marginal positive relation between disagreement and volume for both the number of trades and the futures volume, which would indicate heterogeneity. These results are therefore also not very conclusive.

However, if disagreement is a proxy for heterogeneity but at uncertain times it is a proxy for uncertainty, the relation we observe between disagreement and FX trading volume will be time-varying. In that case, we should also see a strong drop in the relation during the most recent period of turmoil in our sample, from around 2007. We test whether there is a time-varying relation between change in disagreement and trading volume by employing a simple OLS regression estimated with a rolling window, to get time-varying coefficients and confidence bands. A graphical representation of this time-varying relation can be seen in Figure 5.2. We employ a rolling window size of 24 months.

The upper half of Figure 5.2 shows the time-varying relation between disagreement (over the 1 month forecasts) and number of trades for the EURUSD (left) and the USDJPY (right). The results reveal that the relation is indeed time-varying. The results are strongest for the EURUSD. Before 2007, the relation between disagreement and volume is significantly positive. More heterogeneity induces more (noise) trading, and we can therefore say that disagreement was measuring heterogeneity until 2007. However, there is a clear drop in the relation around 2007/2008, when markets started to be more uncertain, after which the coefficient stays significantly negative.

We now turn to our liquidity analyses. Recall that we expect a negative relation between uncertainty and liquidity. Because our measures are actually *illiquidity* measures (a higher bid-ask spread and high-low spread indicate lower liquidity) we expect the relation from Equation 5.4 to be positive if disagreement measures uncertainty.

Table 5.5: Results disagreement and volume

	1m EUR USD	 USD JPY	3m EUR USD	 USD JPY	12m EUR USD	 USD JPY
			volume (no. of trades) - disagreement relation			
constant	-0.0492	-0.1311	-0.0463	-0.1294	-0.0459	-0.1302
	-0.251	-0.8034	-0.2416	-0.7871	-0.2413	-0.7982
disagreement	0.1414	0.1165 *	-0.0622	0.0184	-0.0811	0.1215
	0.7247	1.7559	-0.2322	0.1918	-0.2875	0.7601
adj R2	-0.0036	0.0029	-0.0098	-0.0103	-0.0092	-0.0064
			volume (futures volume) - disagreement relation			
constant	-0.0208	-0.0171	-0.016	-0.0146	-0.0202	-0.0106
	-0.149	-0.1095	-0.1196	-0.0926	-0.1486	-0.0678
disagreement	0.2047	0.2344 ***	-0.1893	0.0849	-0.0342	-0.2599
	1.1663	2.5092	-0.7743	0.7652	-0.1737	-0.9694
adj R2	0.0042	0.0336	-0.0039	-0.0071	-0.0103	0.0047

Results from estimating Equation 5.3, the relation between disagreement and two proxies for trading volume: tick frequency and futures volume. Note that the variables are standardized for ease of coefficient interpretation. T-statistics are displayed under the coefficients (shaded).

Table 5.6: Results disagreement and liquidity

	1m EUR USD	 USD JPY	3m EUR USD	 USD JPY	12m EUR USD	 USD JPY
			liquidity (high-low) disagreement relation			
constant	-0.0546	-0.0332	-0.0638	-0.044	-0.0567	-0.0456
	-0.4759	-0.2225	-0.5465	-0.3189	-0.4276	-0.3388
disagreement	0.3016 *	-0.1122	0.2886	-0.1704	0.0365	-0.1221
	1.8331	-1.0329	1.5737	-1.0755	0.4244	-0.9099
adj R2	0.0954	0.0025	0.0865	0.0173	-0.0088	0.0009
			liquidity (bid-ask spread) disagreement relation			
constant	-0.0535	-0.0552	-0.0644	-0.0447	-0.056	-0.0309
	-0.3867	-0.359	-0.4392	-0.2954	-0.3131	-0.2049
disagreement	0.5935 ***	0.1547	0.5226 **	0.1764 *	0.1916	0.2279 *
	2.5407	1.6149	1.9847	1.664	1.135	1.824
adj R2	0.3406	0.0153	0.2622	0.0207	0.0269	0.0307

Results from estimating Equation 5.4, the relation between disagreement and two proxies for liquidity: high-low spread and bid-ask spread. Note that the variables are standardized for ease of coefficient interpretation. T-statistics are displayed under the coefficients (shaded).

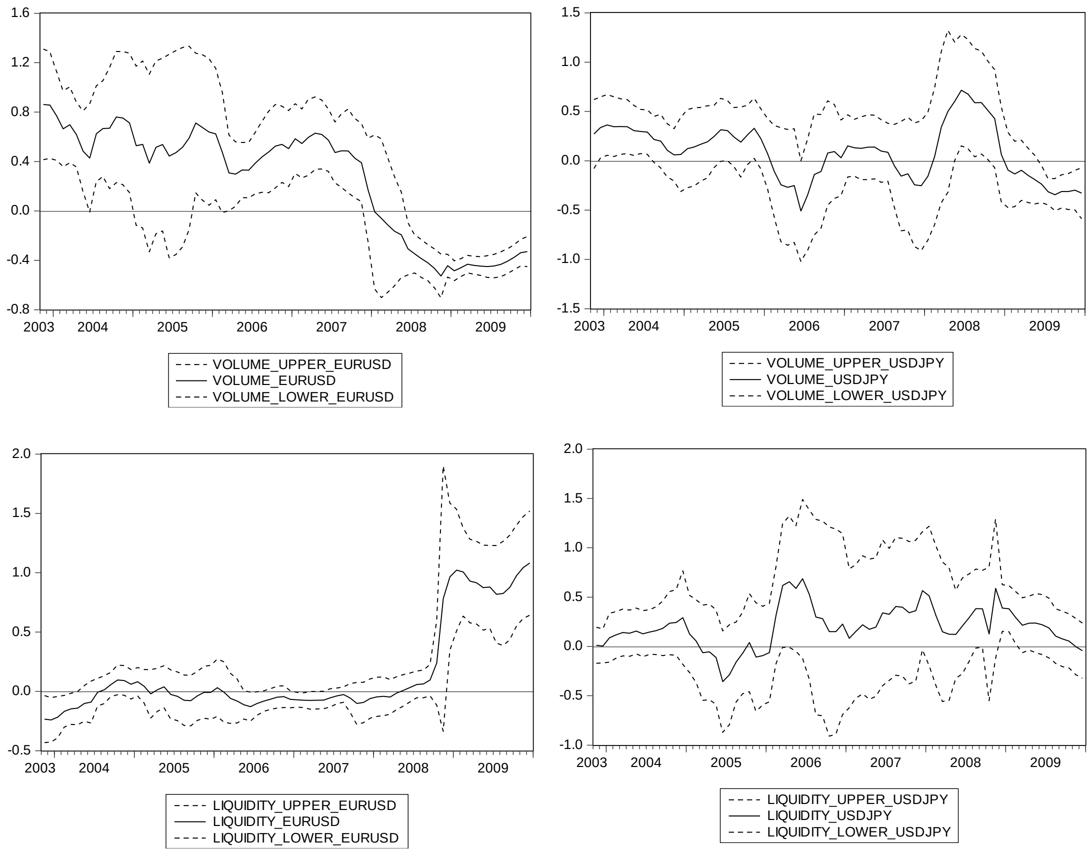

Figure 5.2. Graphical representation of the time-varying relation between disagreement and volume (trade count, upper two graphs), and between disagreement and liquidity (bid-ask spread, lower two graphs).

$$liq_t = \alpha + \beta\psi_t + \varepsilon_t \tag{5.4}$$

The results from estimating Equation 5.4 are displayed in Table 5.6. We can see that there is a positive relation between disagreement and illiquidity for the EURUSD and weakly so for the USDJPY, suggesting disagreement measures uncertainty, at least for EURUSD. However, the earlier results from the VAR suggested that disagreement in the EURUSD measures heterogeneity.

These results are puzzling, but may be explained by the time-varying relationship we already observed for volume. We therefore do the same simple OLS regression estimated with a rolling window of 24 months, to get time-varying coefficients and confidence bands for the relation between disagreement and liquidity (bid-ask spread).

A graphical representation of this time-varying relation can be seen in the lower half of Figure 5.2. We do not find a negative relation between disagreement and liquidity. However, these currency pairs are considered amongst the most liquid, and generally have very low and efficient bid-ask spreads. It is therefore questionable whether more heterogeneity would be able to make these markets even more liquid. However, we do see a very clear rise in the relation during the recent period of turmoil from 2007 to the end of our sample. In this period, the bid-ask spread widens when disagreement increases. This is in support of Hypothesis 3a.

The results from our time-varying regressions reveal that disagreement measures heterogeneity in tranquil times, but increasingly becomes a measure of uncertainty in periods of turmoil. This explains why neither the unconditional VAR, nor the unconditional regressions including volume and liquidity showed clear evidence in favor of any of the hypotheses outlined before.

5.3 Disagreement, risk, and expected returns

Our results from Section 2 show that disagreement is not a stable measure to use for either heterogeneity or uncertainty. However, as summarized in Section 1, there is ample evidence in the literature that disagreement, and uncertainty derived from disagreement, have asset pricing implications. We now turn to testing the implications of disagreement for asset pricing in the time-series of exchange rates. In effect, we focus on the first two moments, expected excess returns and option implied volatility, and test whether disagreement as a measure of uncertainty has explanatory power over the commonly used measure of realized volatility, and whether this relation depends on market turmoil. We first explain how we obtain the relationships between expected returns, risk, uncertainty and volatility, and then continue to test these.

5.3.1 Expected returns and risk

It is by now widely understood that the relation between exchange rate movements and interest rate differentials (uncovered interest parity) is distorted by a risk premium, a premium that international investors demand for the risk they bear that the exchange rate moves against them (Fama, 1984; Engel, 1984; Menkhoff et al., 2012):

$$E[\Delta s_{t+1}] = i - i^* + \rho_t \tag{5.5}$$

Because of covered interest parity (CIP: $f_t - s_t = i - i^*$), and by assuming the investor maximizes utility in a mean-variance optimizing way, we can rewrite Equation 5.5 in expected return risk premium (Dornbusch, 1982; Frankel, 1982):

$$E[r_{t+1}] = E[\Delta s_{t+1}] - fd_t = risk_t \times \gamma_t \tag{5.6}$$

where fd_t is the forward discount. Note that in a rational world ($E[\Delta s_{t+1}] = \Delta s_{t+1}$) and for risk neutral investors ($\gamma_t = 0$), there would be no risk premium and uncovered interest parity would hold. Menkhoff et al. (2012) show that these excess returns are indeed a compensation for time-varying risk, as carry trades perform well in tranquil times, but perform very poorly in times of turmoil. They find that global FX volatility is important in explaining the cross-section of excess currency returns. In this chapter we consider the time-variation rather than the cross-section of excess returns and risk. We also adopt a broader concept of total risk where we consider both volatility and uncertainty as risk components.

$$\rho_t = risk_t \times \gamma_t = F\{\sigma_t, \psi_t\} \tag{5.7}$$

Decomposing risk in a component related to volatility and a component related to uncertainty is motivated by and based on earlier work from Lahiri et al. (1988), Giordani and

Soderlind (2003) and Huisman et al. (2011). This approach of aggregate market risk is micro-based, and thus starts from an agents' subjective probability distribution.

In forecasting future foreign exchange returns $E[r_{t+1}]$, each agent is driven by its own subjective probability distribution function with mean μ_i and variance σ_i^2. Note that these (theoretically) correspond to an agent's point forecast for the future return and its expected volatility. The average expected volatility of the market then corresponds to $E(\sigma_i^2) = \frac{1}{N}\sum_{i=1}^{N}\sigma_i^2$. If agents are assumed to be homogeneous in their expectations the only risk they would face is the volatility of foreign exchange returns. However, the evidence for heterogeneous beliefs in financial markets is overwhelming (see, among others, Frankel and Froot, 1987; Jongen et al., 2012; Ter Ellen et al., 2012) and therefore we need to incorporate a component to account for disagreement among agents. After all, if the distance between forecasts is very large (i.e. agents heavily disagree about their point forecasts) this will increase market risk about future exchange rate movements. Giordani and Soderlind (2003) and Huisman et al. (2011) show theoretically that aggregate risk in a market with heterogeneous expectations is equal to the sum of average expected volatility, $E(\sigma_i^2)$, and the cross-sectional variance, i.e., disagreement, of return expectations. This brings us to the following decomposition of risk:

$$risk_t = E(\sigma_i^2) + \sigma_{\mu_i}^2 \qquad (5.8)$$

In words, the *total risk* of the market is a sum of the average expected volatility and the disagreement among investors about expected returns. This equation mainly differs from Giordani and Soderlind (2003) in the left-hand side component, where we have replaced the variance of the aggregate distribution with a more general term (total) 'risk'. Giordani and Soderlind (2003) mention that interpreting the aggregate distribution is not straightforward for inflation forecasts. However, as Huisman et al. (2011) point out, in financial markets we can interpret the aggregate distribution as a measure of total risk in the market.

As pointed out by Anderson et al. (2009), because volatility is persistent, precise estimation is possible by sampling returns over relatively short time intervals. The drift component, however, requires a very long data interval rendering it difficult to obtain an efficient estimate due to structural breaks. Hence, asset returns are risky due to the deviations from the mean (i.e., volatility) but they are uncertain because the unconditional mean is unknown. Therefore, they argue, dispersion in the expected mean is a reasonable proxy for uncertainty. We follow their interpretation and argue that the dispersion in beliefs, $\sigma_{\mu_i}^2$, equals market uncertainty, given by ψ_t. This is partly backed up by our former analyses in Section 2.

The foreign exchange risk premium, decomposed into risk and risk aversion, is a function of volatility σ_t and uncertainty ψ_t of future exchange rate returns. Former research has shown the importance of accounting for uncertainty in the context of risk premia. Beber et al. (2010) find that uncertainty has a large impact on currency risk premia. Anderson et al. (2009) focus on equity markets and show that uncertainty is more important in explaining the equity risk premium than volatility.

Many studies have measured risk or uncertainty in a narrow way, taking only known unknowns into account, by using volatility models such as GARCH, squared returns or historical variance, which are all based on historical returns. However, such measures underestimate the total risk underlying the market. Anderson et al. (2009) show that uncertainty is even more important in explaining the equity risk premium than volatility.

5.3.2 Estimation and results

We now turn to studying the relations given by (6) - (8) empirically in order to determine the relative importance of volatility and uncertainty for risk and risk premium measures in the foreign exchange market. Our empirical analysis consists of linear regressions (OLS) to estimate the relation between different features of foreign exchange risk premia on the one hand and volatility and disagreement on the other hand.

5.3.2.1 Expected return risk premium

First, we study the expected return risk premium, based on survey data of exchange rate expectations. We may not find very strong results due to the nature of foreign exchange returns: positive returns for one side of the market mean negative returns for the other side.

$$E[\Delta s_{t+h}] - f_t = \alpha + \beta\sigma_t + \gamma\psi_t + \varepsilon_t \qquad (5.9)$$

Table 5.7: Results expected risk premium

	EURUSD			USDJPY		
1m	(1)	(2)	(3)	(1)	(2)	(3)
constant	-0.0008	-0.0007	-0.0008	-0.0036	-0.0035	-0.0035
	-0.5609	-0.4645	-0.5653	-1.5538	-1.481	-1.5216
disagreement	0.002		0.0021	0.0031 **		0.0026 *
	1.452		0.9033	2.1744		1.72
realized volatility		0.0012	-0.0002		0.0025	0.0017
		1.3362	-0.1277		1.1257	0.7519
adj R2	0.0127	-0.0014	0.0023	0.0214	0.0088	0.0192
3m	(1)	(2)	(3)	(1)	(2)	(3)
constant	-0.0032	-0.003	-0.0033	-0.0034	-0.0039	-0.0032
	-1.5829	-1.3232	-1.6425	-1.0617	-1.0566	-1.0255
disagreement	0.0054 ***		0.0065 ***	0.0106 ***		0.0098 ***
	3.0143		2.6213	4.2072		3.807
realized volatility		0.0028 **	-0.0017		0.0058 *	0.0031
		2.225	-0.8393		1.8985	1.1911
adj R2	0.0987	0.0191	0.0949	0.1768	0.0461	0.1829
12m	(1)	(2)	(3)	(1)	(2)	(3)
constant	-0.0058	-0.0056	-0.0059	0.0073	0.0062	0.0084
	-0.9797	-0.9452	-0.992	1.0222	0.9244	1.3371
disagreement	0.005		0.0061	0.0188 ***		0.0175 ***
	0.9741		1.1353	2.821		2.949
realized volatility		0.0007	-0.0024		0.0181 ***	0.017 ***
		0.2285	-0.6561		3.6266	4.0965
adj R2	0.0146	-0.0099	0.0085	0.1467	0.1735	0.3014

Results from estimating Equation 5.9, the impact of disagreement and realized volatility on the expected return risk premium. Note that the explanatory variables are standardized for ease of coefficient interpretation. T-statistics are displayed under the coefficients (shaded).

Table 5.8: Results implied volatility

	EURUSD			USDJPY		
1m	(1)	(2)	(3)	(1)	(2)	(3)
constant	-0.063	-0.0494	-0.053	0.0093	0.0335	0.03
	-0.7024	-0.738	-1.0057	0.0791	0.1993	0.2824
disagreement	0.8248 ***		0.4267 ***	0.6977 ***		0.6203 ***
	7.023		5.444	7.1796		5.3699
realized volatility		0.8587 ***	0.5476 ***		0.4667 ***	0.2776 ***
		14.4625	7.1072		4.1524	3.4856
adj R2	0.6974	0.76	0.8472	0.48	0.1903	0.5401
3m	(1)	(2)	(3)	(1)	(2)	(3)
constant	-0.0876	-0.0494	-0.0655	0.0459	0.0335	0.0641
	-0.8842	-0.738	-1.2583	0.3201	0.1993	0.48
disagreement	0.8026 ***		0.3925 ***	0.6551 ***		0.5709 ***
	5.1338		5.6842	4.4955		3.5673
realized volatility		0.8587 ***	0.592 ***		0.4667 ***	0.3072 ***
		14.4625	9.7408		4.1524	3.8542
adj R2	0.6497	0.76	0.8419	0.3928	0.1903	0.4675
12m	(1)	(2)	(3)	(1)	(2)	(3)
constant	-0.0851	-0.0494	-0.0589	0.0461	0.0335	0.0776
	-0.5877	-0.738	-0.9669	0.2597	0.1993	0.4784
disagreement	0.5885 ***		0.2155 ***	0.4179 ***		0.3847 ***
	3.9389		2.9278	2.6377		2.6579
realized volatility		0.8587 ***	0.7519 ***		0.4667 ***	0.4435 ***
		14.4625	11.6136		4.1524	4.2781
adj R2	0.3512	0.76	0.7944	0.1195	0.1903	0.2925

Results from estimating Equation 5.10, the relation between implied volatility, disagreement and realized volatility. Note that the variables are standardized for ease of coefficient interpretation. T-statistics are displayed under the coefficients (shaded).

Table 5.9: Results implied volatility for heterogeneity versus uncertainty

	1m				3m				12m			
	EURUSD		USDJPY		EURUSD		USDJPY		EURUSD		USDJPY	
constant	-0.15189	***	-0.036143		-0.145143	***	0.029527		-0.100786		0.114958	
	-2.576791		-0.326926		-2.661501		0.23628		-1.576136		0.661353	
heterogeneity	0.150068		0.142544	*	0.138053		0.048257		0.081921		-0.095632	
(base effect)	1.524335		1.948118		1.203376		0.537685		1.104975		-0.614226	
realized volatility	0.532843	***	0.480041	***	0.538471	***	0.56715	***	0.58769	***	0.722205	***
(base effect)	5.863339		4.300885		5.725202		4.170642		4.845296		3.791618	
uncertainty	0.469629	***	0.690449	***	0.357388	***	0.78053	***	0.226514	*	0.673006	***
(marginal effect)	3.263335		6.232559		2.396209		4.349247		1.904722		2.679875	
realized volatility turmoil	-0.110284		-0.243084		0.009577		-0.235667		0.163033		-0.248545	
(marginal effect)	-0.874925		-1.602059		0.077453		-1.393196		1.142746		-1.097405	
adj R2	0.864444		0.620866		0.85292		0.56548		0.80952		0.337225	

Results from estimating Equation 5.10, the relation between implied volatility, disagreement and realized volatility. The base period is the period from 2001 to 2007, and represents the period in which disagreement measures heterogeneity. The lower part of the table shows the marginal ("added") effects for the period from 2007 to 2010, when disagreement measures uncertainty. Note that the variables are standardized for ease of coefficient interpretation. T-statistics are displayed under the coefficients (shaded).

The results of estimating Equation 5.9 can be found in Table 5.7. Disagreement has a significant relation with the expected return risk premium for all horizons for USDJPY, and for the three month horizon for EURUSD. This indicates that to some extent, investors want to be compensated for uncertainty or the risk of heterogeneous beliefs. These results are promising for our total risk analyses, as we will not have the same problem with the two-sidedness of the market as we have with analyzing returns.

5.3.2.2 Total risk

Next, we study the relation between total risk, disagreement, and realized volatility. We proxy total risk with implied volatility. The implied volatility of an asset is the risk-neutral volatility implied from an option pricing model such as the Black and Scholes (1973) model. Due to the fact that investors in real life are risk averse, realized volatility is generally smaller than implied volatility. Therefore, implied volatility can be seen as a purer and more direct measure of the total risk in the market. Ajinkya and Gift (1985) were among the first to analyze risk and dispersion of financial analysts' earnings forecasts. They state that implied volatility measures are superior to historical measures of volatility because implied volatility also captures analyst dispersion (which they state is a contemporaneous measure of stock variability). Therefore, the relation between total risk (implied volatility), disagreement, and realized volatility is studied:

$$\sigma_{IV,t} = \alpha + \beta\sigma_t + \gamma\psi_t + \varepsilon_t \tag{5.10}$$

The results are shown in Table 5.8. Because disagreement and realized volatility are highly correlated, we replace ψ_t from Equation 5.10 with the residual of regressing disagreement on realized volatility in model (3). We can see that realized volatility is positively related to implied volatility, as expected. More interestingly, uncertainty, measured by disagreement, has a large and significant effect on implied volatility beyond the impact of realized volatility. Note that the variables are standardized and we can therefore compare models (1) and (2) over variables, horizons, and markets. The obtained coefficients are qualitatively and quantitatively consistent between the EURUSD and USDJPY markets. We neither confirm nor reject the results of Anderson et al. (2009), who conclude that uncertainty is a more important component in explaining the risk-return relationship. However, the impact of disagreement is substantial, with coefficients from regression (1) ranging from 0.4197 to 0.8248 and from 0.3330 to 0.5895 for regression (3). Moreover, adjusted R-squares from regression (3) are all between 0.6945 and 0.9207, which means that the combination of volatility and uncertainty explains a very large part of the variance of implied volatility. Furthermore, we can see that the effect of disagreement is strongest if we use disagreement from 1 month forecasts, and weakest if we use the 12 month disagreement.

Finally, we split our sample in two by including a dummy variable that is zero from the start of our sample until the beginning of 2007, and one from 2007 to the end of our sample, to capture the possible time-variation in the interpretation of our disagreement measure. As the relation between disagreement and implied volatility should stem from it being a measure for uncertainty, we expect the relation to be strongest for the second part of our sample, and weaker or nonexistent for the first part. Results can be found in Table 5.9.

We can indeed see that for all horizons and both currency pairs, disagreement is only related to implied volatility in the turmoil period. This confirms our earlier results indicating that disagreement measures heterogeneity in tranquil times and uncertainty during turmoil.

5.4 Conclusion

In this chapter we have investigated the dual usage of disagreement as a measure for heterogeneity and uncertainty, and the added value of this measure in explaining risk and risk premia. Although arguments for disagreement being a measure of heterogeneity or uncertainty are appealing for both interpretations, they may in times have different (asset pricing) implications. For example, they have different and perhaps even opposing effects on trading volume and liquidity, and the timing of their effect is different. It is therefore important to analyze whether the time-variation in disagreement mainly measures time-variation in heterogeneity or time-variation in uncertainty.

To investigate whether disagreement is mostly measuring uncertainty or heterogeneity, we made use of the timing of the disagreement-volatility relation and the impact of heterogeneity on trading volume. More heterogeneity induces more noise trading, which leads to higher levels of volume and volatility. The relation between heterogeneity and volatility should therefore be running from heterogeneity to volatility. The relation between uncertainty and volatility can be seen as a contemporaneous one – volatility is often even used as a measure or proxy for uncertainty. In times of high uncertainty, asset volatility is generally higher. Alternatively, financial market participants may become more uncertain about their point forecasts when volatility is high. In that case, the relation runs from volatility to uncertainty. Our VAR estimation did not provide us with convincing results for either of the two hypotheses. This can also be said about the findings from our unconditional trading volume and liquidity analyses. Whether there is a positive (negative) relation between disagreement and volume (illiquidity) depends on the time-period. In tranquil times, the relation between disagreement and volume is positive, and there is no significant relation between disagreement and liquidity. In such times disagreement is thus a proper measure of heterogeneity. However, in times of turmoil, higher disagreement is followed by lower volume and lower liquidity. We can therefore say that in such times, disagreement measures uncertainty.

After having analyzed when the time-variation in disagreement mainly measures time-variation in uncertainty or time-variation in heterogeneity, we tested whether it has any explanatory power for risk and expected risk premia beyond (the more traditional uncertainty measure) volatility. We find that investors want to be compensated for both uncertainty and volatility, and that there is a very strong relation between implied volatility and disagreement. This relation remains strong after controlling for realized volatility. As we can expect, this relation only holds for the second part of our sample, when disagreement measures uncertainty.

Our contribution to the current literature is twofold. First of all, we unfold the important finding that disagreement is not a stable measure for heterogeneity, nor for uncertainty, and that we need to take into account whether we are in a turmoil market state or not when interpreting this measure. We also show that in such states it measures a substantial part of risk that is not covered by volatility, a traditionally used measure of uncertainty, and in that function explains variation in risk and expected risk premium.

Future research could further investigate the use of disagreement in different market states (tranquil and turmoil), from different underlying fundamentals (such as interest rates), and for a large cross-section of currencies. When using an unconditional measure of disagreement, one should be wary of the fact that there is not a clear interpretation of disagreement that holds in different states of the market.

6 Conclusion

6.1 Main findings

This dissertation has shed more light on the dynamics, measurement, and implications of heterogeneous beliefs in financial markets. In doing so, I have tried to merge two strands of literature by using concepts from the agent-based finance literature and combining those with more conventional framing in the general (behavioral) finance literature. I want to stress that there is room for improvement in linking these different strands of literature that try to tackle problems in a similar way but work almost completely parallel to each other. For example, what the agent-based literature labels as a 'chartist' is often labeled as a 'momentum' trader in the general finance literature, and what is labeled as a 'PPP' or 'UIP' strategy in the latter is often labeled a 'fundamentalist' strategy in agent-based modeling.

However, considering the different names given to the types of investors or types of forecasting strategies, there is a growing literature that rejects the notion of rational homogenous investors. We have learned from this dissertation that investors are not only heterogeneous, they also do not use stable, unconditional, forecasting rules to form their expectation on future movements of exchange rates. Instead, they may change the way they form expectations based on various factors, such as the past performance of different forecasting rules or the horizon for which they form their expectations. The dynamics between the different types of investors can cause periods of severe mispricing and disruption of financial markets. Survey datasets that contain analysts' forecast are important tools to unravel investor expectation mechanisms and dynamics that can otherwise not always be directly observed in the data. They can also reveal why investors sometimes disagree more with each other than at other times and how the differences of these reasons can be of crucial importance for market dynamics.

By analyzing such a survey dataset in Chapter 3, I find that there is a lot of heterogeneity in the beliefs and forecasting behavior of investors. Investors in foreign exchange markets use past changes, PPP rates and interest rates to form their expectations. Momentum trading especially occurs for short horizons, whereas PPP trading is more common for longer horizons. The interest differential is used on all horizons but primarily for long-horizon forecasting. We find indications that agents have a stronger tendency to apply a carry trade (UIP) expectation at the shorter (longer) forecast horizon. Interestingly, there are also differences in expectations within different strategies. Some investors expect past trends to continue and therefore positively extrapolate past returns into future forecasts (bandwagon). Others expect past trends to revert. There are investors who use the interest differential as a tool for carry trade; that is, they expect an appreciation of the currency of the high-interest-rate country. There are also investors who believe in UIP and therefore expect a depreciation of the currency of the high-interest-rate country. Furthermore, a long history of positive returns seems to influence investors when forming their expectations, making them more vulnerable to bandwagon expectations. A long history of undervaluation of an exchange rate can cause a loss of faith in reversion to the fundamental value. The results I presented in this chapter are, on the one hand, a strong confirmation of theoretical statements and empirical findings from the behavioral finance literature. On the other hand, they are an extension to the literature, as I have shown that there is also important heterogeneity within the strategies.

With a similar framework as used in Chapter 3, I analyze the sovereign CDS market during the European sovereign debt crisis in Chapter 4, and find that heterogeneity and dynamics in the composition of market beliefs have played a large role in the mispricing of sovereign credit risk during this episode. This chapter addresses the question of whether the recent movements in European sovereign credit spreads are driven by weakened fundamentals and/or momentum trading behavior. In order to do this, a fundamental default spread is first calculated by means of regressing past hazard rates on a set of sovereign default determinants and using the resulting fitted values. Furthermore, to better explain the dynamics of sovereign CDS spread movements, a heterogeneous agent model with two key types of expectation formation rules and time-varying weights is estimated using market spreads and fundamentals-based spreads. The estimation of this heterogeneous agent model reveals that in most European sovereign CDS markets both fundamental and momentum expectations played a role. In peripheral countries fundamental expectations were dominated by momentum throughout the crisis period contributing to the observed higher spreads. Momentum trading exerted a destabilizing effect on the market by prolonging price trends. In some cases, fundamental expectations pulled the market spreads back to their fundamental-based level, thereby stabilizing CDS spreads. The change in the market weights of these two expectations coincided with larger market movements and both movements towards and away from the fundamentals implied-spread. For the five troubled peripheral countries, momentum trading played a much more dominant role in increasing their sovereign CDS spreads beyond the levels justified by weakening fundamentals.

Whereas I have shown ways in which investors in the foreign exchange and sovereign CDS markets can be heterogeneous and how this changes conditional on certain variables in Chapter 3 and Chapter 4, I evaluate a commonly used measure for the level of heterogeneity in Chapter 5. Disagreement has become a widely used measure to account for both investor heterogeneity and uncertainty, and a solid conclusion about the different interpretations of disagreement has not been reached. In this chapter I assess the usefulness of the variable to be used as a measure of either one, by utilizing the codependency between disagreement and volatility and the different effect that heterogeneity and uncertainty have on foreign exchange trading volume and liquidity. Using the full sample of observations, I do not find evidence for either one of the hypotheses and therefore employ measures to reveal possible time-variation in the relation between disagreement and volume or liquidity. These results suggest that the time-variation in disagreement measures time-variation in heterogeneity in tranquil times, but becomes a good measure of uncertainty during a period of turmoil. After having established this, I analyze whether disagreement has added value over realized volatility when linking it to risk and risk premium. I find that disagreement indeed has explanatory power for risk and risk premium beyond realized volatility, and that its impact is sometimes even larger than the impact of realized volatility. Moreover, I find that disagreement is only linked to total risk in times of turmoil, whereas realized volatility has a constant relation with total risk. This confirms the earlier result that disagreement only measures uncertainty in periods of turmoil.

However, we can see from the results in Chapter 4 that the finding that disagreement mainly measures uncertainty in periods of turmoil does not mean that there is no heterogeneity in such periods.

With these chapters, I have completed the trinity of dynamics, measurement, and implications of heterogeneous beliefs in financial markets. Although all three themes come back in some form in every chapter, the chapters each have their own focus. In Chapter 3, I have focused on the dynamics of heterogeneous beliefs. Chapter 4 reveals some of the implications that heterogeneous beliefs can have for financial markets. And, finally, Chapter 5 analyzes a broadly used variable to measure heterogeneous beliefs.

6.2 Looking ahead

Naturally, this dissertation also has some shortcomings. For issues that arise when estimating heterogeneous agent models, such as parameter instability, calculating fundamental values, and the functional form of the switching function, I would like to refer to Chapter 8 of Zwinkels (2008), in which these are extensively discussed. I would rather like to focus on bridging gaps in the literature. As I stated at the beginning of this chapter, one of the aims of this dissertation was to link heterogeneous agent models from the agent based literature to other models in the behavioral finance literature that model heterogeneous beliefs. Although heterogeneous agent models have been very successful in explaining market dynamics in a wide range of financial markets (see Chapter 2), the majority of papers developing, simulating, or estimating these models are published in quite specialized journals and are therefore mainly read by a very specific group of people. In my opinion this is partly caused by the choice of terminology. Whereas the agent-based literature often speaks of 'chartists' and 'fundamentalists', the (behavioral) finance literature rather speaks of 'technical analysis' or 'momentum' for the former type of agent or investor, and of the respective fundamental model (e.g. PPP or UIP) used for the latter type. To link those streams of literature I have used the latter formulation in models that are otherwise quite standard heterogeneous agent models. Moreover, many people find it hard to believe that there are two substantially and perhaps even fundamentally different types of agents who 'easily' change their type once they can be more profitable in the role of the other type. A commonly heard argument is that 'fundamental' investors (say, for example, Warren Buffet) will always be fundamentalists and will never change their 'religion' to chartism. I acknowledge and to some extent share this concern, and believe that it is important to stress that a more realistic way of thinking about such models is that there are different agents who all use those two (or more) strategies to form their expectations, and that they apply different and dynamic weights to these strategies. In such a framework, there can be 'hardcore' fundamentalists who will never use technical analysis in their expectation formation process, and pure chartists who do not bother to gather information on fundamentals but rather look at trends, moving averages, and candle sticks. The majority of the agents will be somewhere in between, adding some weight to their fundamental strategy when that has performed well in the (recent) past, and shifting more weight to forecasts arising from technical analysis if that has proven to be profitable.

I believe this interpretation is crucial, because I think our main aim should be to model behavior of market participants in a more realistic way, with the underlying goal of modeling financial markets in a more realistic way. In that context, I also see a lot of potential for linking some of the agent-based literature to the microstructure literature. The latter focuses on what the microstructure of a certain market looks like, and what kind of implications this has for the price dynamics in these markets. Whereas both streams of literature are micro-based, the agent-based literature starts from modeling the behavior of agents in a realistic way, and the microstructure literature aims to understand the market structure and the actions of its participants in a more realistic way. A potential alley could be to test predictions from heterogeneous agent models on (high frequency) micro data such as order flow and trading positions.

In more general terms, I feel that there should be more room for interdisciplinary research. Progress can be made by linking different sub-fields of finance and economics to each other, but even more interesting is the integration with and application of insights from completely different fields, such as physics, biology, psychology, and sociology. In effect, the field of behavioral economics would not exist without such interactions, and often the most revolutionary findings come from those who succeed in applying ideas, theories and frameworks from one field to another. One characteristic from research in fields such as physics and medicine is the cooperation between research teams. Whereas cooperation between four or five people is already quite unique in economics, research in medicine is sometimes published with an author list exceeding 50 people, and some research in quantum mechanics yields papers with author lists exceeding 3000 people. Perhaps the economics profession could use a bit of this attitude of cooperation to tackle recurrent problems (such as financial crises) in a more effective way.

In light of these shortcomings of the profession, there is room for improvement in linking different strands of literature that try to tackle problems in a similar way but work almost completely parallel to each other. In the process of writing this dissertation I have experienced that one sometimes needs to be satisfied with taking tiny steps in the right direction. When cooperating on a larger scale, the progression may be larger than the sum of these tiny steps.

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Summary

This dissertation is part of a growing research field in which the heterogeneity of economic actors is incorporated. It bundles four studies that consider the measurement, dynamics and implications of heterogeneous beliefs in financial markets, using a variety of datasets. The studies show that investors are not only heterogeneous, they also do not use stable, unconditional, forecasting rules to form their expectation on future movements of financial markets. Instead, they may change the way they form expectations based on various factors, such as the past performance of different forecasting rules or the horizon for which they form their expectations. The dynamics between the different types of investors can cause periods of severe mispricing and disruption of financial markets. Survey datasets that contain analysts' forecast are important tools to unravel investor expectation mechanisms and dynamics that can otherwise not always be directly observed in the data. They can also reveal why investors sometimes disagree more with each other than at other times and how these underlying reasons can be of crucial importance for market dynamics.

Nederlandse samenvatting

Dit proefschrift maakt onderdeel uit van een groeiend onderzoeksdomein waarin de heterogeniteit van economische actoren in acht wordt genomen. Het voegt vier studies samen waarin de meting, dynamiek en implicaties van heterogene opvattingen in financiële markten worden getoetst, met behulp van verschillende soorten datasets. De studies tonen aan dat beleggers heterogeen zijn en geen onvoorwaardelijke strategieën gebruiken om hun verwachtingen te vormen over toekomstige onwikkelingen in financiële markten. In plaats daarvan vormen ze tijdsvariërende verwachtingen op basis van een verscheidenheid aan factoren, zoals de in het verleden behaalde resultaten van de verschillende strategieën of de horizon waarvoor zij hun verwachtingen vormen. De dynamiek tussen de verschillende soorten beleggers kan markten uit evenwicht brengen en perioden creëren waarin financiële instrumenten te laag of juist te hoog gewaardeerd zijn. Survey datasets waarin de prognoses van beleggers worden gevat, kunnen bruikbare informatie bevatten over de verschillende manieren waarop beleggers hun verwachtingen vormen. Met behulp van dit soort datasets kan onderzocht worden waarom beleggers het soms meer of minder met elkaar eens zijn, en hoe de onderliggende redenen daarvoor cruciaal kunnen zijn voor de dynamiek van financiële markten.

About the author

Saskia ter Ellen was born on February 6th, 1987 in Strijen, The Netherlands. She graduated from Radboud University Nijmegen with a Bachelor degree in Economics in 2009, after having been active as a board member of 'Economische Studenten Vereniging' in 2006/2007 and 'United Netherlands' in 2008/2009. In the summer of 2009 she moved to Rotterdam to complete a Master in Financial Economics at the Erasmus School of Economics, and stayed there to obtain a PhD degree under the supervision of Willem Verschoor and Remco Zwinkels. During her PhD Saskia spent four months at University of Technology Sydney to work with Carl Chiarella, Xue-Zhong He and Eliza Wu. She presented her work at numerous conferences and seminars. In her fourth year she organized the 'Research in Behavioural Finance Conference' in cooperation with Martijn van den Assem and Remco Zwinkels, which will be the first in a biennial sequence due to its overwhelming success. She has supervised various master theses, was a teaching assistant for the BSc course 'Financial Methods and Techniques' and co-developed and taught the intensive MSc course 'Seminar Behavioural Finance'. Chapters 3 and 4 of this dissertation have been published in respectively 'Journal of International Money and Finance' and 'Journal of Empirical Finance'. Besides these academic accomplishments, one of her main accomplishments during the years of her PhD was finishing the Rotterdam Marathon in April 2013. Saskia currently lives in Oslo, where she works as a Research Economist in the research department of Norges Bank, Norway's central bank.

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