Essays on Empirical Market Finance

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Part I

Aims and Scope

Aims and Scope

One of the most central questions in finance is how to evaluate assets. Valuation methods provide guidance to investors when choosing which assets to include in their portfolios, and in which proportions. They also allow managers to make decisions about the sources and uses of funds in their firms.

The classical framework, to which we will refer as neoclassical finance, built on the 50s, relies on strong assumptions about the rationality of the individuals who populate the markets. These agents are able to use all available information to make correct inferences, and update their beliefs according to Bayesian updating rules. They make choices that maximize their intertemporal utility. They trade in markets which are competitive, complete, and liquid. It is in this setup that the main theorems of asset pricing are obtained, in which only systematic, non-diversifiable risk is priced. Holding a riskier asset should bring comparatively higher returns, which is the equivalent of saying there are "no free lunches", or alternatively, that the only way to achieve returns is to accept some degree of risk.

This view of finance has provided easily actionable models that are well-functioning, and present the advantage of being firmly grounded in theory. An essential part of their attractiveness resides in the fact that they are obtained, through deduction, from axioms that have normative appeal. However, it is undeniable that the predictions formulated in these models do not always match the actual behavior observed in financial markets.

What are some of those elements that collide with the beautiful picture of agents and markets envisioned in neoclassical finance?

To begin with, there is too much trading volume around. In the standard models, agents should trade very little between themselves, to the point that some authors have proposed what are referred to as "no trade theorems" (Milgrom and Stokey, 1982). Observed levels of volatility are also too high compared to theoretical expectations, as pointed out in Shiller (1981). The Equity Premium Puzzle of Mehra and Prescott (1985) shows that the return differential between equities and bonds cannot be explained by risk alone.

Of particular interest to us in this thesis are two areas in which empirical observations prove difficult to reconcile with theoretical predictions: the difficulty to describe the risk and return relationship in the standard framework, and the apparent lack of risk exposure found in the stock returns of multinationals.

Such results, termed anomalies, are not consistent with the established asset-pricing theories. Indeed, a result is only anomalous in relative terms to a model that describes the expected result. In the first two empirical investigations, we will show how certain risk-sorted portfolios, in particular market states, display patterns that are not compatible with standard asset pricing results.

Our contribution revolves around two main components.

First, our focus will be on the notion of disagreement, by which we designate the dispersion of beliefs, or the divergence of opinions, among investors, concerning the value of an asset. This concept has been the topic of promising empirical investigations, but in the context of stock returns, disagreement is most often measured at the stock-level (Diether et al., 2002; Chen et al., 2002; Sadka and Scherbina, 2007; Bali et al., 2016). We hypothesize that it is relevant to consider disagreement also as an indicator of the market-wide investor mood, in a manner reminiscent of the notion of sentiment. There have been a large number of studies which consider the impact of optimistic vs. pessimistic periods on the risk-return relationship (Brown and Cliff, 2004, 2005; Baker and Wurgler, 2006; Stambaugh et al., 2012; Antoniou et al., 2016), and which bring attention to the fact that such mood swings can impact market dynamics. Surprisingly, there is a lack of empirical investigations which consider disagreement in a similar manner [1]. It is more widespread in macroeconomics, where disagreement (and its possible link with uncertainty) is considered in the context of inflation forecasts and exchange rate markets, but so far, less so in the context of stock returns. We will leverage market-wide measures of disagreement in all three of our empirical works: in Chapter 2, in Chapter 3 where we will consider its impact jointly with sentiment, and in Chapter 4 in the context of the risk exposure of multinationals.

Second, we will take an interest in recent developments to extend the classical, one-factor CAPM, and see what insight can be gained from the decomposition of returns framework of Campbell and Shiller (1988b,a). The intuition is that the value of a stock portfolio can vary because of news related to future cash flows, and also because of news related to the discount rates that will be applied to discount those cash flows. The choice of the methodology used in empirical contexts relies to some extent on the degree of predictability of stock returns,

[1] Notable exceptions include Hong and Stein (2007); Hong and Sraer (2016).

and is thus influenced by the ongoing debate in this area[2]. In Campbell and Vuolteenaho (2004), the authors extend this decomposition of the market return in two components to the CAPM, and show that its beta can also be decomposed in a cash flow beta and a discount rate beta. Using a Vector Autoregression (VAR) approach, as in Campbell (1991), to operationalize the decomposition of returns, they are able to shed new light on an empirical puzzle that had been a thorn in the side of finance practitioners since Fama and French (1992): small stocks and value stocks seem to display patterns in their returns that are not related to their beta. They argue that the higher returns for value stocks and small stocks[3] can be explained by higher loadings on cash flow beta, which carries a higher price of risk[4].

We propose to leverage the additional insights brought by the decomposition of returns framework, in conjunction with market-wide measures of disagreement and sentiment, to gain a better understanding of the relationship between risk and return. Given that they do not seem to agree with standard asset-pricing frameworks, our results indicate either that these frameworks are not able to appropriately represent reality. In that respect, such findings might entice searchers to refine models to incorporate elements that are suspected of being significant, and so far comparatively neglected. They could also indicate market inefficiencies, which, under the condition that they are economically significant enough, could be exploited by arbitrageurs. However, as Schwert (2003) points out, anomalies have a tendency to disappear, either because they have been arbitraged away, but also possibly because their detection was dependent on a specific period being investigated. Even more simply, their appearance might be due to purely random factors. While we strive to address these concerns to the best of our abilities, their invitation to some level of prudence in possible extrapolations is duly heard.

The outline of this thesis is as follows. In Chapter 1, we propose to provide a survey centered around the concept of disagreement, which plays an important role in the rest of our empirical essays. We aim to provide an overview of where our understanding of the notion of disagreement fits in the existing literature of behavioral finance, putting the emphasis on its essential features. An important issue we then discuss is how to measure disagreement. We then consider existing results on the relationship between disagreement and stock returns, both on the theoretical side and on the empirical side, before ending the chapter with some thoughts on the link between disagreement, sentiment, and uncertainty.

[2] On that topic, a recent excellent summary is provided in Cochrane (2011).
[3] As in Fama and French (1992).
[4] A result obtained by extending the ICAPM model of Merton (1973).

Of capital interest in our first two empirical investigations is the relationship between risk and return. In the neoclassical framework, this relationship is described using the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965), wherein only one factor, the beta of an asset with the market portfolio, should summarize a stock's risk. This simple relationship has proven most elusive in empirical works: other factors than beta have proven to matter in explaining the cross-section of stock returns (Banz, 1981; Basu, 1977, 1983; Fama and French, 1992). Additionally, higher beta stocks have proven that they do not deliver higher returns than lower beta stocks (Baker et al., 2011; Frazzini and Pedersen, 2014).

In Chapter 2, with a sample of 2,085 firms, we investigate how disagreement interacts with the decomposition of returns framework, in the context of the investigation of the risk return relationship. We build our measure of disagreement on the basis of analysts' forecasts, a choice that is extensively motivated by the literature (Fried and Givoly, 1982; O'brien, 1988; Abarbanell et al., 1995). We build a market-wide measure of disagreement, in a spirit similar to Yu (2011); Hong and Sraer (2016). We follow the decomposition of returns using a VAR methodology, following Campbell (1991); Campbell and Mei (1993); Campbell and Vuolteenaho (2004), and leveraging some recent developments such as Chen and Zhao (2009); Chen et al. (2013) concerning the choice of variables to include in the state vector. Given that, in a large portion of the existing literature on disagreement, authors have used stock-level dispersion of forecasts, we also investigate to which extent our results would compare to that approach.

A legitimate concern for results obtained with a *disagreement* measure, in a literature dominated by empirical investigations about the effect of investor *sentiment*, is whether the results obtained are possibly a manifestation of that other, more well-known, and better documented factor. In Chapter 3, we propose to address that concern, and we consider in conjunction the impact of sentiment and disagreement, using for the former the time series proposed by Baker and Wurgler (2006). An analysis of risk premia in different market states also follows.

In Chapter 4, we consider risk and return in another context, that of firms' exposure to risk factors, and in this case, the exposure of US multinationals to foreign exchange risk. There are well-documented reasons to lead us to expect that investors should incorporate in their valuation models the impact of exchange risk on firms: Shapiro (1975) is among the first and most influential, followed by Dumas (1978); Hodder (1982), but also Flood Jr and Lessard (1986); Hekman (1985), and, from a microeconomic point of view Levi (1994) and Bodnar et al. (2002). What is surprising is that this exposure is hard to find in the data, for instance in the works of Jorion (1990); He and Ng (1998); Griffin and Stulz (2001), who find at best mixed results in that regard. Adler and Dumas (1984) emphasize that *unanticipated* foreign exchange movements should have an impact of firm value. To build a measure of anticipation, researchers often rely on experts' forecasts. The hypothesis we put to the test in this chapter is whether the information content of these forecasts is dependent on the disagreement among experts who formulated it. In a way, our approach propose an articulation in the foreign exchange exposure literature of ideas from other works which consider how the quality and precision of information received by investors can influence stock returns, as in Veronesi (2000) or Zhang (2006).

Chapter 5 summarizes the main findings of this thesis and presents some possibilities for future research.

Part II

Context

Chapter 1

A survey on behavioral finance and disagreement

1.1 Preliminary notes

Our aim in this section is to position some key concepts in the existing literature, starting from a view as broad as possible, and progressively delving in greater detail. Doing so will enable, we hope, the readers to better understand on which level we follow the classical framework of empirical finance, on which level we stray apart, and the extent to which our approach follows or departs from previous investigations.

In the rest of this chapter, after a few words on neoclassical finance and its main assumptions, we propose in Section 1.2 a quick overview of the role of anomalies in finance, followed by a brief discussion of the contribution of behavioral finance in that area. Then, in Section 1.3, we will focus in greater detail on the concepts of sentiment and particularly disagreement in the context of behavioral finance. Finally, in Section 1.3.5 we will share a few thoughts on sentiment.

1.2 Neoclassical finance and anomalies

1.2.1 Neoclassical finance

The traditional framework in which practitioners have sought to understand financial markets, and which is sometimes referred to as "neoclassical finance", has had its main foundation laid out the 50s and the 60s. It is built on the following assumptions. First of all, the representative agents in financial markets can be understood as rational, homogeneous individuals, who make correct inferences based on the information they receive, and act upon them in a way that is consistent with intertemporal utility maximization notions. Additionally, it is generally assumed that there are no arbitrage opportunities available.

There are many advantages to the conceptual simplicity of this approach. It allows the building of a formal architecture which, in turn, allows the derivation of formal theorems. The first of two of the most important is the Fundamental Theorem of Asset Pricing, which maintains that the following assertions are equivalent : absence of arbitrage, existence of a consistent positive linear pricing rule, and existence of an optimum for an agent who prefers more to less. The other is the Pricing Rule Representation Theorem, which posits that the positive linear pricing rule mentioned above can be formulated using state prices, risk-neutral expectations, or state-price density.

The analysis of standard portfolio choice problems[1] obtains classical results, which are still influential and widely used among finance practitioners, such as optimal portfolio choice models, and asset pricing models, chiefly the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT).

1.2.2 Anomalies

Empirical investigations of the markets sometimes deliver findings that do not agree with the expectations of the established models. These "anomalies" might indicate either that the underlying models need to be modified to better reflect reality, but they might also point to market inefficiencies, which would contradict the Efficient Market Hypothesis (EMH), but not necessarily mean that the models need revising. Fama (1970), points out that tests of market efficiency actually always perform a joint test on the underlying models.

Documented anomalies tend to disappear after they have been documented in the literature. The question that arises is whether this is due to the fact that the anomaly, while real, has been exploited by smart investors and arbitraged away from the market, or alternatively, that there was not much of an anomaly to begin with, maybe because its detection was a statistical aberration[2].

Several of these anomalies are as follows:

The trading volume that can be observed is much too high to be explained in a model in which agents are rational, and should in theory trade very little. Even accounting for liquidity or rebalancing needs does not allow for the rationaliza-

[1] In which, to sum up briefly, we want to derive portfolio holdings and consumptions, to maximize utility of consumption, under the budget constraint.

[2] Campbell et al. (1997) describe what they term data snooping, the fact that with so many researches incentivized to find anomalous patterns in data, standard statistical methods to establish significance do not provide accurate results, and propose methods to correct for the over-reporting of statistically significant findings.

tion the immense trading volumes observed. Another, often related matter, is that of volatility, that is to say that prices of financial assets are more volatile than what we should expect in the classical, rational and efficient world.

There are predictable differences in returns across assets: Banz (1981) document, for instance, that small-capitalization firms earn higher average returns that what is predicted by the Capital Asset Pricing Model (CAPM) of Sharpe (1964); Lintner (1965). Basu (1977) finds that value firms, i.e., firms with high earnings-to-price ratios, also earn returns that are not consistent with CAPM expectations. Similarly, Lakonishok et al. (1994) find that value strategies, which consist of buying stocks that have low prices relative to accounting measures outperform the market. Jegadeesh and Titman (1993) find that there is some momentum in stock returns, and that past winners outperform past losers on an annual basis.

In the cross-section of stock returns, the CAPM tells us that no other factor than an asset's beta should be able to explain its returns. Many deviations from this have been extensively documented through the years, with Fama and French (1992) among the most well-known, in which both size and and a scaled-price ratio, book-to-market, are found to create patterns in the cross-section of stock returns. Fama and French (1993) incorporate these anomalies into the asset-pricing model. The standard CAPM beta itself does not deliver the expected results when considering the security market line, which depicts the relationship between risk and returns, with riskier stocks failing to deliver higher returns in a series of results starting with Black (1972) and Black et al. (1972).

Thus, while the traditional framework has provided results that form the foundations of finance, there does seem to be sufficient concerns to warrant investigating deviations from its main assumptions.

Behavioral finance

Behavioral finance can be understood as an attempt to incorporate biases and limitations, identified in social psychology into asset-pricing theories, by relaxing the rationality of agents. We can distinguish two main avenues of investigation, that form the two pillars of behavioral finance: firstly, the aforementioned limitation of the rationality of investors, through psychological factors, and secondly, the consideration of possible limits to arbitrage[3].

There are two ways for an investor's *psychology* to exert an influence that leads to a behavior that would be considered irrational in the classical framework.

[3] Some designs incorporate either one of these aspects, others the two in conjunction.

The first crucial component is how agents form expectations based on information, or beliefs. Psychologists have identified several biases in the belief formation process : overconfidence, the fact that people overestimate the precision of their estimates, overoptimism (or wishful thinking), or anchoring, to cite but a few.

Alternatively, even if we assume that investors update their beliefs in efficient and unbiased ways, they might act upon them with decision rules that do not conform to the standard expected utility framework, with von Neumann-Morgenstern preferences. One of the most famous deviation from the standard preferences is the one proposed in Kahneman and Tversky (1979). They consider a form of weighted utility in which people have differential preferences to monetary gains than losses, displaying a disproportionately large aversion for the latter.

The second pillar of behavioral finance rests on *limits to arbitrage*, that is to say, the hurdles met by agents to exploit arbitrage opportunities in markets. Indeed, in a world composed at least partly by investors with psychological biases, and who henceforth provide price signals that deviate from what rationality would dictate to be fundamental values, how come other, smart arbitrageurs would not be able to exploit this mispricing and bring the price back to sanity?

Researchers have identified mechanisms that would prevent such arbitrage opportunities to be taken advantage of. Shleifer and Vishny (1997) show how risky and prohibitively costly it can be to try to exploit a mispricing. Restrictions on the capacity of investors to adopt short positions are one of the main ways through which limits to arbitrage are manifest, be it, for instance, regulatory considerations for mutual funds, or psychological considerations for individuals, as in Barber and Odean (2008).

1.3 Disagreement and sentiment

One issue with the term *disagreement* is that it can tend to mean quite different things to different people, which can create a non-negligible risk of confusion.

Quite simply, in accordance with most of the literature, we define disagreement as the fact that some investors hold a different opinion regarding the value of a financial asset[4].

In the framework of classical finance, there is little room for any notion of disagreement. Consider a conservative interpretation: market activity generates

[4] In some papers, the concept is referred to as "difference of opinion", "divergence of opinions", with very similar or identical interpretations.

information, which is delivered simultaneously to all market participants. Those participants are thought to be rational agents (or at least, that the representative participant can be construed as a rational agent) who use the same model to interpret the received information. They in turn form identical beliefs, upon which they act according to standard preferences.

Those investors are thus considered to correctly, and identically, evaluate financial assets. Consequently, as mentioned above, this has led some researchers, as in Milgrom and Stokey (1982), to develop theoretical models based on rational expectations in which all the information available in the market is communicated through price changes, and consequently, when an equilibrium is reached, no trade should ever occur, even when agents receive private information, a result which is known as the "no-trade theorem". Other related models can be found in Rubinstein (1975) and Hakansson et al. (1982).

Such a result was of course meant as a way to underline the interest that lied in the development of models which are able to account for the inescapable fact that investors do trade, and in high volumes (at the very least, with respect to the prediction that a "no-trade" theorem delivers). Such developments have been made in Varian (1989), Harris and Raviv (1993) and Kandel and Pearson (1995), but their models put the emphasis on trying to generate volume patterns, which do not necessarily have a significant impact on prices.

1.3.1 Sources of disagreement

That there is some level of disagreement among market participants is, on a practical manner, subject to little to no debate, be it because of the observed volumes of trade, of because of general intuition and anecdotal observation of financial markets.

What are the processes through which disagreement might arise among market participants? A first possibility lies in the way information is transmitted to them. News might indeed not arrive simultaneously for all market participants. This can be due to a number of reasons, for instance, information might be costly to acquire[5], or alternatively, some investors might just pay more attention to specific news than others, for instance professional traders specialized in a specific industry. This concept has been used in Hong and Stein (1999) to show how a model with gradual information flow could explain the momentum effect. A very close conceptual approach is that of limited attention in investors, which put more emphasis on the limited cognitive abilities of the representative investor to

[5] As in Rothschild and Stiglitz (1976) among others.

correctly incorporate all available information in her decisions, see for instance Hirshleifer and Teoh (2003) in which attention is drawn to the form of the information presented to the investor, or Peng and Xiong (2006) who show that investors tend to process more market and sector-wide information than firm-specific information.

Intuitively, it is easy to see how the concept of limited attention can create disagreement among market participants, who simply do not share the same signal on which to form their beliefs. However, a question is then raised : when realizing that a number of market participants appear to possess better information, and after observing the trades on the markets, how come other investors do not update their beliefs accordingly?

To answer that question, apart from pointing to the fact that an investor who is already cognitively overloaded to such an extent that she cannot process all publicly available information can hardly be expected to leverage the information available in trading activity[6], one interesting notion is that of *overconfidence*. Without overconfidence, rational investors should learn from each other's trades, even if they have different information sets, or to put it as John D. Geanakoplos[7], "We can't disagree forever". Overconfidence means that investors overestimate the precision of their own estimations and underestimate the information content available to them on the market. They in essence, neglect that they are possibly in the situation of informational disadvantage encompassed hereinabove[8][9].

It thus could be that all information does not arrive simultaneously, or that agents do not pay equal attention to all available information. Another possibility might also be, that even if the information set is shared among market participants, they differ in their inference-making processes because they do not share, for instance, the same economic models to interpret that information. In Kurz (1994), the author builds a model in which agents do not have structural knowledge of the market, and develop individual beliefs with the same access to data. Far from reducing disagreement, as is sometimes proposed, investors, once confronted with new and identical information can still end up disagreeing even more than before, as has been shown in Harris and Raviv (1993) and Kandel and Pearson (1995), if they have different models that lead them to different interpretations.

Finally, even if agents would form the same beliefs on the basis of the mar-

[6] A justification that in a sense would bring us back to the concept of limited attention again.
[7] Geanakoplos and Polemarchakis (1982).
[8] The interlinking between overconfidence and limits to learning is put forward in Peng and Xiong (2006).
[9] On the psychological foundations of overconfidence, we refer to the classical works in Tversky and Kahneman (1975).

ket information they receive, they might act upon those in different ways. As mentioned above, deviations from von Neumann-Morgenstern preferences of rational choice. Some traders might also be characterized as risk-loving, as for instance envisioned by Tirole (1982).

The growing literature on heterogeneous agents models (HAM), of which an extensive review can be found in Hommes (2006), provides another example of agents with different decision-making processes. A typical setup involves some proportion of traders who trade on the fundamental value of financial assets, with noise traders, who trade on short-term patterns. A classical example is De Long et al. (1990).

Finally, even in the traditional portfolio optimization setup, differential initial endowments, coupled with diversification motives, may induce different levels of desirability across market participants for the same asset.

1.3.2 Measures of disagreement

Even though models have been built that incorporate the key features that we want the notion of disagreement to possess, it still leaves open the question as to how, in an empirical finance framework, one should try to *measure* disagreement. Models are often silent as to which measurable features of individual investor behavior or aggregate market features should be considered to capture the effect of disagreement.

Ideally, what we would like to have is an estimate of the probability distribution for each individual investor. In a theoretical framework, conceptual tools of information theory could then be used to consider disagreement. This possibility is raised by Zanardo (2016) to apply tools developed to measure the distance between two probability distributions, such as the Kullback- Leibler divergence[10] and the Bhattacharyya distance[11] on the study of disagreement.

Such a theoretical approach does not provide any guidance for our choice of an empirical proxy for disagreement, as the sort of information about beliefs that would be required to leverage this methodology is not easily available to the researcher, neither in a survey framework nor in an experimental context, which we will not discuss here.

What we do have, however, is a subset of investors, whose work precisely involves communicating to the public information about their market expectations: professional analysts. Given that there is a wide range of analysts who provide forecasts, about stock market relevant data such as earnings, or foreign exchange

[10] Kullback and Leibler (1951).
[11] Bhattacharyya (1946).

markets, one could use this set of forecasts as a proxy for the unobservable distribution of beliefs among all investors.

Assessing the appropriateness of analysts' forecasts as a proxy for disagreement is not a straightforward task, as we do not really have a true, ex-post measure of disagreement with which we could compare our proxy. Answering that question involves making assumptions as to which other measure you were aiming for to begin with.

That being said, there have been attempts to objectify the relevance of the use of forecasts in that context. Fried and Givoly (1982) compare the performance of analysts' forecasts to time series models to forecast earnings, and find the former more accurate. O'brien (1988) reaches the same conclusion in a very similar endeavour. Abarbanell et al. (1995) consider the reactions to earnings surprises, and find analysts' forecasts satisfactory, if not perfect, proxy for investor beliefs.

Researchers have rightfully brought the attention on several limitations that should be kept in mind when using analysts' forecasts in the context of stock markets. They are prone to several biases, mainly overoptimism, as pointed out in Hong et al. (2000), Lim (2001) and Jackson (2005). Note at this stage that biases in the *level* of the forecast are a much lesser concern when it is a notion of *dispersion* of forecasts that is of interest to the researcher.

1.3.3 Disagreement and Uncertainty

At this stage we take the opportunity to discuss the notion of uncertainty, and how it interfaces with disagreement. In most conceptions, uncertainty is a concept in a close semantical neighbourhood of disagreement, with often the interpretation that establishing the presence of disagreement can be used to infer that there is some uncertainty around, as we shall discuss in greater detail when discussing disagreement measures. Given the close proximity of the concepts, and the fact that the related words are sometimes used in the literature in a manner that does not allow the reader to easily distinguish the topic at hand, we propose the following clarification.

The conventional definition of uncertainty traces back to Knight (1921), in which a distinction between risk and uncertainty is proposed. *Risk* occurs when the future is not known, but the probability distribution of the possible futures is known. The classical comparison is that of a casino, in which the players know the odds of the game. *Uncertainty* occurs when the probability distribution is not known. Further complication, and the beginning of a link with disagreement, arises when one considers that in this case, different investors might hold different estimates of that unknown probability distribution. Sometimes, the word *ambiguity* is helpfully used to refer to situations of uncertainty, such as in Heath and Tversky (1991), a practice that unfortunately does not seem to have caught on.

Motivations to take an interest on the concept of uncertainty abound in many fields, not only in asset pricing, where a widely accepted result posits that people have a stronger dislike for uncertainty than they do for risk[12], but also in the study of foreign exchange markets, or in macroeconomics.

In a way, disagreement and uncertainty are two concepts which are not necessarily linked, and which empirical researchers would like to investigate. Both lack a direct measurement method, and accordingly, both tend to rely on proxies. The dispersion of analysts forecasts is an promising proxy for both concepts, which can lead to some difficulty whent it comes to interpreting findings where the dispersion of forecasts was used a proxy. Different models, however, are built to leverage the information that lies in uncertainty and disagreement, and these models lead to different testable hypotheses.

A wide array of papers have, consequently, taken interest in whether disagreement is, or not, an appropriate proxy for uncertainty. This is facilitated by the fact that it is comparatively somewhat easier to build alternative measures for uncertainty with which to compare the estimate based on disagreement, for instance using a time series approach, or in the case of financial markets, implied volatility indices.

Among the first to conclude that disagreement might be a relevant proxy for uncertainty is Zarnowitz and Lambros (1987), in the context of inflation forecasts. On the other side of that argument, we find Bomberger (1996), who point out that while the *mean expectation* of forecasters can be taken as a proxy for the representative agent's mean expectation, there is no theoretical grounding, and therefore it is more controversial, to assume that the *variance across forecasts* could be used as a proxy for uncertainty, which they define as the conditional variance of inflation about a particular forecast, that is to say, a measure of how far off that forecast turned out to be. Another investigation on the role of disagreement about future inflation is proposed by Mankiw et al. (2003). In Rich and Tracy (2010), little evidence is found for a link between dispersion of inflation forecasts, taken as a proxy for disagreement, and uncertainty.

This debate in macroeconomics is spilling into the accounting and empirical finance literature, as for instance in Barron and Stuerke (1998) and Abarbanell et al. (1995), where the authors try to investigate to which extent dispersion in analysts' forecasts reflects uncertainty. Lahiri and Sheng (2010) use a standard de-

[12] Barberis and Thaler (2003).

composition of forecast errors into common and idiosyncratic shocks. They find that the difference between uncertainty and disagreement is the perceived variance of future aggregate shocks that accumulate over forecast horizons, which implies that the robustness of the relationship between uncertainty and disagreement depends on the variance of aggregate shocks over time. In periods with large volatility of aggregate shocks, disagreement is less useful as a proxy for uncertainty.

Anderson et al. (2009) are interested in building an asset pricing model that includes two risk factors, one featuring risk, the other uncertainty. They measure uncertainty using the disagreement of among analysts in the Survey of Professional Forecasters. They describe conditions under which they can guarantee that uncertainty is proportional to disagreement, but point out that in reality, the beliefs of forecasters may be influenced by new information in different ways.

Buraschi et al. (2014a) study the impact of heterogeneous perceptions among agents on bond and stock returns. They build an aggregate disagreement risk factor using factor-mimicking portfolios, and find that it is priced in the cross section of bond and stock returns. Buraschi et al. (2014b) use a similar methodology to investigate the cross-section of option returns. In these papers the interest is in finding whether disagreement risk matters in asset pricing.

A recent work is Ter Ellen et al. (2016), where the authors compare disagreement, measured as the dispersion in forecasts among expert dealers on foreign exchange markets, and find that disagreement is best understood as a proxy for heterogeneity rather than for uncertainty, as the latter relationship does not prove stable through time, a finding that is consistent with Lahiri and Sheng (2010).

Persistence of disagreement

Even if we consider a market in which some subset of the investors hold biased beliefs, in the sense that they do not conform to rational expectations, what prevents some other part of investors, who hold a correct, unbiased, estimation of the fundamental value of a financial asset, from exploiting this arbitrage opportunity, and in so doing, correct the mispricing? Indeed, apart from detailing how some level of disagreement can appear on the market, one needs also to consider how this disagreement can persist and exert an influence on prices.

One factor that we already mentioned is that of *limited learning*, mechanisms which explain why agents are not leveraging all the information available to them in trades. Another possibility is to consider *limits to arbitrage*.

Shleifer and Vishny (1997) show that exploiting arbitrage opportunities is not a riskless affair, and that there are circumstances in which arbitrage strategies prove ineffective. It may be, for instance, that before the price gets back to a level closer to its fundamental value, the mispricing widens : if some portion of investors have managed to influence the price, nothing, in the short run, prevents them from pushing the price even further from its fundamental value, and thus force the tentative arbitrageur to suffer a loss, which he might not be able to cover, exiting the market, and worsening the mispricing[13].

In the disagreement literature, limits to arbitrage are often envisioned through the lens of short-selling constraints. These are motivated by the fact that some proportion of market participants do no short as much as they should, whether because they are prevented from doing so, as is the case for mutual funds (and documented in Almazan et al. (2004)), or because, in the case of individuals, they tend to only consider selling the stocks that they own, as shown in Barber and Odean (2008). Lamont and Stein (2004) demonstrate that, at the market level, aggregate short positions are too low and do not play a stabilizing role.

One particularly influential reference is Miller (1977), in which a model of a market with some degree of divergence of opinion[14] is developed, resulting in more optimistic and more pessimistic investors, coupled with short-selling constraints. In this model, under such circumstances, when disagreement rises, pessimists are progressively crowded out of the market, given that they are prevented from transmitting their signal to the market due to their inability to take short positions. Under disagreement, this logic would lead us to expect some level of overpricing.

Miller (1977) considers a one-period setting. Harrison and Kreps (1978) develop a related model of speculative behavior with divergence of opinions, but this time in a multi-period model.

1.3.4 The impact of disagreement on stock returns

Armed with a good candidate for a proxy of investors' disagreement, there has been interest in confronting theoretical models about the nature of the relationship between disagreement and stock returns with stock market data[15].

[13] Essentially the argument in De Long et al. (1990).

[14] Which, the author already mentions in this comparatively early paper, might be the result of asymmetrical information.

[15] We emphasize again that empirical approaches suffer from the fact that there subsists a level of debate about the choice of the dispersion of analysts' forecasts as a proxy. Arguments can be raised concerning the exact nature of the effects captured by this measure, and whether it proxies for uncertainty or not. Similarly, one can object that the effects are merely the manifestation of some other variable, that was not included in the model. In most settings, for instance, disagreement occurs via asymmetrical information among investors and limits to arbitrage. The effect of these two factors then becomes, in a way, mingled in the proxy for disagreement. Accordingly, one should be careful either to address this possible concern in her empirical design,

Both on the theoretical and empirical side, the literature appears indecisive as to the effect of disagreement: does it drive prices up, and returns down, or vice versa?

Theoretical models that lead to an expected positive relationship between returns and disagreement have been proposed by Varian (1989), who finds that the asset with the more dispersion of beliefs, i.e., subject to the most disagreement, will have the lower equilibrium price, in a market where all agents have identical tastes. Abel and Others (1989) find that increased heterogeneity in beliefs reduces the stock price.

In an early investigation, Cragg and Malkiel (1968) and Malkiel and Cragg (1970) had already gathered some support for the hypothesis that high disagreement brings higher returns, as does Harris (1986). This also finds support in the more recent work of Boehme et al. (2009) and Avramov et al. (2009), and also in Carlin et al. (2014), even though in that last case, they investigate specifically the market for mortgage-backed securities, and use as an empirical proxy for disagreement the prepayment speed of mortgages.

Arguments for expecting a negative relationship between disagreement and returns owe a lot to the model of Miller (1977) in which, when disagreement arises, optimists dominate the market while pessimists are left out, and prices tend to be overevaluated. Putting the accent on the speculative impulse, the model has been extended in a multiple periods setting by Harrison and Kreps (1978), in which agents pay prices that exceed their own valuation, and in a similar argumentation, in Morris (1996), in which investors anticipate being able to resell to another, even more optimistic investor, before learning takes place, and hinders the progress of the speculative process at hand. Scheinkman and Xiong (2003), still in that lineage, develop a model in which overconfidence and short-sale constraints lead to asset price bubbles characterized by high trading volume and high price volatility.

Empirical support for the Miller (1977) hypothesis has been extensive. Diether et al. (2002) find that stocks for which the stock-level dispersion of EPS forecasts is higher underperform other stocks. Chen et al. (2002) consider a similar environment of dispersion of beliefs and short-sale constraints, with the particularity that they use the breadth of ownership, a measure of the proportion of long position for a particular asset, to proxy for the severity of short-sale constraints, and find that tighter constraints are associated with lower returns. Goetzmann and Massa (2005) find that dispersion of opinion is negatively related to future returns, Park (2005) find that it has predictive power for lower returns at interme-

or keep in mind the that the reach of their conclusions might be limited.

diate horizons, Hong et al. (2006) build a model in which heterogeneous beliefs and limited float combine to create speculative bubbles. Finally, Bali et al. (2016) propose a model in which idiosyncratic shocks to a stock's volatility due to unusual news flow increase the level of disagreement about the firm value, and are associated to lower returns.

Finally, Doukas et al. (2006) advocate, in a way, for a middle ground between the two camps, and say that the impact of disagreement on stock returns is actually dependent on the *sign* of the forecast: in their results, overpricing occurs when the forecasts are positive, but the reverse is true when forecasts are negative.

1.3.5 Sentiment

In the field of behavioral finance, the notion of investor sentiment is much more prominent than that of disagreement, and consequently has been the subject of a broader and more thorough investigation. In this section, rather than aim at any sort of exhaustive presentation, we will briefly try to identify the points where the two show similarities, where they differ, and possibly where they might interact.

Both disagreement and sentiment can be understood as deviations from rational expectations, and neither would exist in a world populated by rational investors who correctly maximize their utility. Recently, Shefrin (2005) proposed a framework in which behavioral finance could be, methodologically speaking, made compatible with the neoclassical setup. In his view, sentiment should be understood as the deviation from the pricing kernel, or stochastic discount factor (SDF), of a market with rational, representative investors, in which prices are efficient[16].

Under such a generalization, sentiment can be understood as encompassing disagreement, if it were not for the fact that, in a first approach, nothing prevents all investors to have the same sentiment function, a situation in which there would of course be no disagreement. The framework, however, easily allows for heterogeneous beliefs, in which different investors have different sentiment functions.

More recently, Barone-Adesi et al. (2013) have proposed an extension of Shefrin (2005), in which they derive a theoretically-based notion of sentiment using options prices. Their setup also allows to discriminate between overconfidence and optimism, with the former concept playing a substantial role in most models of disagreement. Their approach, which provides results consistent with tradi-

[16] More precisely, the core idea put forward is that the log-SDF can be expressed as a sum of sentiment, and two fundamental terms.

tional sentiment measures such as the one of Baker and Wurgler (2006) is illustrative of attempts to unify the field, and goes to show that the the words use to designate deviations from rationality have no definition set in stone.

That being said, such an harmonization under a common methodology has still not happened, and a lot of research is still being conducted using "traditional" conceptions of disagreement and sentiment. What could be said about their linkages in this context?

A key difference between sentiment and disagreement is that the former is almost always a market measure, while the latter is, in a majority of cases, an asset specific measure. There are papers who consider disagreement as a market-wide feature[17], but many seminal results were obtained when considering stock-level disagreement, as for instance in Diether et al. (2002).

Generally, there is an intuitive appeal to the thought that a higher level of sentiment would be accompanied by higher levels of disagreement. If one assumes that some proportion of investors, the smart arbitrageurs, hold beliefs that stay close to the fundamental value no matter the levels of sentiment, we would expect, consequently, a rise in disagreement. Grinblatt and Keloharju (2001) and Lamont and Thaler (2003) find that unsophisticated, or noise traders, are more likely to participate in the stock market during periods of high sentiment, which would, in turn, bring higher disagreement levels.

[17] A concept often put forward by Harrison Hong, see for instance Hong and Stein (2007), or more recently Hong and Sraer (2016).

Part III

Empirical Work

Chapter 2

According to Discord

The Risk-Return Relationship through Disagreement

2.1 Introduction

The relationship between the risk of a financial asset and its expected return is at the heart of asset pricing, and is of utmost importance for finance practitioners and researchers. The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) provides a model to depict this relationship, using market beta as a risk measure, and expecting a positive link between risk and return.

In practice, however, high-risk assets often deliver lower expected returns than low-risk assets, a fact that has led to investigation attempts nearly as old as the CAPM itself. Black (1972) and Black et al. (1972) are among the first to document it. More recently, Baker et al. (2011) have shown that the performance of stocks is actually declining with market beta. What are the factors that might explain this puzzle?

One promising avenue of investigation that has gained a lot of recent attention consists of taking a closer look at the dynamics of disagreement among market participants.

There is no uniform and widely shared definition of disagreement among behavioral finance practitioners. Dispersion of opinion among investors can arise through many different ways, and consequently be conceived as the manifestation of many different phenomena. One of those is that of gradual information flows, with news arriving at different times for different investors, as presented in Hong and Stein (1999) and put to the test in Hong et al. (2000). Another is limited attention, in which some investors focus on a subset of more easily accessible information, as in Barber and Odean (2008). Yet another possibility is that of heterogeneous priors, that is to say, even if all news arrive simultaneously, and all investors pay equal attention to it, there would still be a dispersion in their interpretation of the impact of these news, because investors have different economic models. On this subject, the seminal works are Harris and Raviv (1993) and Kandel and Pearson (1995). A recent review of disagreement and its importance in the analysis of stock markets is proposed in Hong and Stein (2007). As they point out, models built around the notion of disagreement also present the advantage of providing a framework in which both patterns in trade volumes and effects on prices can be reconciled, in comparison with other models which focused on generating trade volume[1].

Typically, it is measured at the stock-level, leveraging the proxy of analysts forecasts[2]. Diether et al. (2002) show that higher stock-level dispersion of earnings forecasts are linked to lower expected returns for a period of up to six months, thus establishing how an individual measure of disagreement can explain market dynamics. Other authors find results that point in the opposite direction. Anderson et al. (2005) find that dispersion factors (portfolios that are long in high dispersion stocks and short in low dispersion stocks) are positively related to expected returns. Qu et al. (2003) also observe a positive relation between a factor for disagreement and expected returns.

There is a growing body of literature that takes interest in the influence of market-wide measures of sentiment on the stock market[3]. The notion of disagreement has been viewed in such a manner to a lesser extent. A notable exception is Hong and Sraer (2016), who build a market-level aggregate time-series of disagreement. They find that in high market disagreement periods, high beta stocks, which are more susceptible to disagreement, experience lower than expected returns.

Another strand of literature takes interest in whether disagreement can represent a priced risk factor in itself. Anderson et al. (2009) use disagreement measures as a proxy for uncertainty, using the quarterly Survey of Professional Forecasters, and a flexible weighting scheme for individual forecasts. They propose that economic agents interpret disagreement as model uncertainty, and obtain that their resulting measure of uncertainty has strong implications in terms of uncertainty-returns trade-off, and in the cross-section, find that the price of un-

[1] As in Varian (1989); Harris and Raviv (1993); Kandel and Pearson (1995).

[2] When considering the use of analysts forecasts to proxy for disagreement, one might want to consider what their biases might be. Reassuring signals include O'brien (1988), who finds that analysts perform better than time series models to forecast earnings, and Abarbanell et al. (1995), who finds that analysts forecasts constitute appropriate proxies for investor beliefs.

[3] A prominent example is Baker and Wurgler (2006)

certainty is significantly positive. Buraschi et al. (2014a) build an aggregate disagreement risk measure on the basis of I/B/E/S forecasts. They construct factor-mimicking portfolios to obtain a risk factor, which they find to carry a statistically significant nonzero factor price of risk.

While there have been some investigations in the impact of disagreement on the risk-return relationship, to our knowledge there have been so far no attempt at trying to gather additional insights in this regard with the help of the decomposition of returns framework, proposed by Campbell and Shiller (1988a,b), and implemented afterwards, among many others, by Campbell (1991) and Campbell and Ammer (1993). In this chapter, we propose an empirical design that attempts to fill that gap, by thus considering the impact of disagreement on the risk-return dynamics, and following Campbell and Shiller (1988a,b), we decompose stock returns in two components, one related to cash flow news, and the other related to discount rate news. Subsequently, using this decomposition framework, and in the spirit of Campbell and Vuolteenaho (2004), we distinguish two components in the traditional CAPM beta: one related to cash flow risk, and the other related to discount rate risk (which in their seminal article they coined, respectively, "bad beta" and "good beta"). In their study, this distinction allows them to provide an explanation for the surprisingly high returns traditionally observed for value (low market-to-fundamentals) and small stocks, which they find carry a higher proportion of cash-flow beta or "bad beta".

Recent empirical designs incorporating the decomposition of returns approach to scrutinize the risk-return relationship can be found in Botshekan et al. (2012), or Garrett and Priestley (2012).

Our results show that to obtain an in-depth understanding of the risk-return relationship on the stock market, one needs not only to consider how disagreement states can influence market dynamics, but also the differential impact disagreement exerts on the decomposed risk measures that are cash flow and discount rate betas.

We leverage both approaches to deliver the insight that in high disagreement periods, high-risk assets deliver lower returns than low-risk assets. This finding is consistent with Hong and Sraer (2016) in which by the fact that higher beta stocks are more susceptible to disagreement, and in the presence limits to arbitrage (in the form of short-selling restrictions), the price signal is transmitted to the market in a disproportionate manner by investors who hold higher valuations, pushing prices up, and returns down. These findings are also consistent with the Miller (1977) hypothesis that, since divergence of opinion is likely to increase with risk, expected returns may be be lower for risky securities. Accordingly, both in the case of cash flow and discount rate betas, we observe a downward-sloping relationship between returns and risk.

In periods associated with lower levels of aggregate disagreement, however, the impact is differentiated: with respect to cash flow betas, i.e., risk related to unexpected news related to dividends, we observe a positive, upward-sloping curve. In this situation, risk seems appropriately priced by market participants, leading to lower prices and higher returns. In the case of discount rate betas, results point to an two-piece curve, showing an inverted U-shape, with higher discount rate betas stocks being associated to lower returns after a certain point.

Our paper is structured as follows. In Section 2.2, we describe our data collecting process, detail the empirical procedures we used, and relate them to existing works. In Section 2.3, we will provide an exploration of our results, and put them in perspective with previous literature. Section 2.4 concludes.

2.2 Methodology

2.2.1 Sample Construction

The main source for the data used in this paper is S&P Capital IQ. We start from a sample of 27,719 publicly listed US companies. We remove those for which Capital IQ ends up returning an error, and obtain 27,253 companies. We remove the companies for whom there never was more than 4 analysts, which amounts to 20,612 companies, and obtain a new total of 6,641 companies. We remove those for which, if there was analyst coverage, it was by fewer than four on average, a criteria which is met for 1,910 companies in our sample. Our new total is 4,731 companies. 2,538 of them do not have the US dollar as both their listing currency, and the currency used for their estimates reporting.

From the remaining 2,193 companies, following Jegadeesh and Titman (2001), we do not include in our sample stocks for which the valuation is below USD 5, in order to ensure that our results are not overly driven by small and illiquid stocks, or by the bid-ask bounce. Several identifiers return error codes for all or part of their data when queried in the database, and are thus also removed. Our final sample is composed of 2,085 companies.

2.2.2 Decomposition of Returns

The Return-Decomposition Framework

In their seminal article, Campbell and Shiller (1988a,b) posit that two separate elements can be discerned in the data generation process of stock returns, in the form of news impacting the market that are related to future dividends, and news that are related to future rates of return. They are respectively referred to as cash flow and discount rate news.

Most of the subsequent research has been performed using market-level estimates of cash flow and discount rate news, for instance Campbell and Ammer (1993) and Campbell (1991), in which the analysis was on the part of the total unexpected returns' variance that was attributable to each of the two.

It is of note that it is possible to study the impact of firm-specific cash flow and discount rate news, for instance Vuolteenaho (2002) has done so to distinguish which of the two sources has the largest influence on a firm's stock returns[4].

This methodological approach and the following derivations are owed to Campbell and Vuolteenaho (2004); Chen and Zhao (2009); Chen et al. (2013).

The idea that unexpected stock returns can be approximated by a linear combination of cash flow (CF) news and discount rate (DR) news has been first posited by Campbell and Shiller (1988a). In line with Campbell (1991), we use the following loglinear approximate decomposition of returns:

$$\begin{aligned} e_{t+1} &= r_{t+1} - E_t r_{t+1} \\ &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \\ &= e_{CF,t+1} - e_{DR,t+1} \\ &= N_{CF,t+1} - N_{DR,t+1} \end{aligned} \tag{2.1}$$

where r_{t+1} is the equity return and E_t is the expectation operator at time t, ρ is a constant close to but lower than 1, and d_t is the dividend growth rate. We then decompose the market portfolio, with e_{t+1} being the unexpected market return, and $e_{CF,t+1}$ and $-e_{DR,t+1}$ its CF news and DR news components.

In the following, the time subscript is suppressed when possible. The market beta is defined as

$$\beta_i = \frac{Cov(e_i, e)}{Var(e)} \tag{2.2}$$

[4] A more recent stream of research in the accounting literature concerned with firm-level of cash flow and discount rate news includes Callen and Segal (2004), Callen et al. (2005) and Callen et al. (2006).

where e_i is the return of asset i. Similarly to the market portfolio, it can be decomposed into two elements:

$$\beta_i = \frac{Cov(e_i, e_{CF})}{Var(e)} + \frac{Cov(e_i, -e_{DR})}{Var(e)} = \beta_{i,CF} + \beta_{i,DR} \tag{2.3}$$

where $\beta_{i,CF}$ and $\beta_{i,CF}$ are, respectively, the CF beta and DR beta for asset i.

In the empirical implementation, Campbell and Vuolteenaho (2004) assume that a vector of state variables, z_{t+1}, which we will discuss in greater detail, are generated by a first-order vector autoregression (VAR):

$$\begin{aligned} z_{t+1} &= \Gamma z_t + u_{t+1} \\ r_{t+1} &= e1' z_{t+1} \end{aligned} \tag{2.4}$$

where z_{t+1} is a $k \times 1$ state vector with r_{t+1} as its first element, Γ is a $k \times k$ matrix of coefficients, $e1$ is a vector whose first element is equal to one and zero otherwise, and u_{t+1} is a vector of serially independent random shocks. The unexpected market return at time $t+1$ is then the first element of u_{t+1}, i.e. $e1'u_{t+1} = u_{t+1}$.

Through recursive substitution of Equation (2.4) in Equation (2.1), we obtain the following for CF news and DR news:

$$\begin{aligned} -N_{DR,t+1} &= -e1'\lambda u_{t+1} \\ N_{CF,t+1} &= (e1' + e1'\lambda) u_{t+1} \end{aligned} \tag{2.5}$$

where $\lambda = \rho\Gamma(I - \rho\Gamma)^{-1}$, . The gist is that, because of the predictability of the expected return (through the VAR), surprises in the current state variables will be incorporated into the expected return for every future period, through the term $-e1'\lambda u_{t+1}$.

Then,

$$\beta_{i,CF} \equiv (e1' + e1'\lambda) \frac{Cov(e_{i,t}, u_t)}{Var(e)} \tag{2.6}$$

$$\beta_{i,DR} \equiv -e1'\lambda \frac{Cov(e_{i,t}, u_t)}{Var(e)} \tag{2.7}$$

where $Cov(e_{i,t}, u_t)$ is a vector of covariance between firm i's stock return and the innovations in the state variables.

Empirical Implementation using the VAR methodology

In our calculations, and following Campbell and Vuolteenaho (2004), we make two adjustments. First, we use excess returns in the VAR and the calculation of betas. Second, we include one lag of the market news when calculating the betas in order to mitigate the stale-price problem.

The cash flow β for asset i is thus calculated as follows

$$\widehat{\beta_{i,CF}} = \frac{\widehat{Cov}(r_{i,t}, \widehat{N}_{CF,t})}{\widehat{Var}(\widehat{N}_{CF,t} - \widehat{N}_{DR,t})} \tag{2.8}$$

. The denominator is the variance of unexpected market returns, $Var(\hat{e})$. The corresponding discount rate beta is

$$\widehat{\beta_{i,DR}} = \frac{\widehat{Cov}(r_{i,t}, -\widehat{N}_{DR,t})}{\widehat{Var}(\widehat{N}_{CF,t} - \widehat{N}_{DR,t})} \tag{2.9}$$

Of crucial importance in the empirical implementation is the choice of variables to include in the vector z_t. In theory, the decomposition of returns as proposed by Campbell and Shiller (1988b) works soundly. In practice, the methodology depends on the ability to provide good instruments to estimate both return components.

Our approach, which entails estimating discount rate news and backing out cash flow news is the most commonly used in the literature[5]. It provides a way to sidestep the issue that one would have with estimating the data cash flow news in monthly (or higher) frequency given the seasonal nature of dividends. While it has been widely and successfully used, it also has considerable drawbacks, identified among others by Chen and Zhao (2009). Return predictability regressions often have small predictive power, are extremely sensitive to the choice of variables (in the VAR case for instance, in the choice of state variables to include in the z_t vector). Backing out CF news means from the difference between total returns and discount rate news inevitably means that any misspecification error in the estimation of discount rate news is bound to trickle down in the estimation of cash flow news, compounding its impact.

As they point out, the motivation for the variables to include in the VAR should come from outside the model. In practice, authors sometimes purposefully try a large combination of variables in order to find the most fruitful combination, which then gives credence to the accusation of the "fishing license" critique made by Fama (1991).

With the hope of circumventing part of the disadvantages brought by backing out cash flow news from a necessarily flawed discount rate news estimate, Chen and Zhao (2009) or Garrett and Priestley (2012), advocate a direct estimation of both cash flow and discount rate news, a method which is theoretically

[5] Among others, Campbell (1991); Campbell and Ammer (1993)

appealing but also requires necessary and costly compromises when it comes to actual implementation. Campbell et al. (2010) propose a virulent rebuttal of that critique.

Another crucial parameter to consider when implementing is the choice of the period of estimation for the VAR, with a large number of existing research in this area focusing on the different results obtained when estimating the VAR in various different subperiods [6].

Given that no agreed upon consensus has emerged from the debate with regards to the methodology, we resort to using in our analysis what we we think is a compromise that presents the advantage of providing, if not exactly a wide agreement, at the very least what can be considered a basic and robust approach. We thus choose to estimate discount rate news, and in a second stage back out cash flow news. To estimate discount rate news, we use VAR for which the state vector includes variables put forward in a recent implementation in Chen et al. (2013)[7]. These are dividend growth, the dividend-price ratio, and $eqis$, which corresponds to *Percent Equity Issuing*, i.e. the ratio of equity issuing activity as a fraction of total issuing activity[8].

2.2.3 Disagreement Measures

We are interested in the manner by which disagreement affects the relationship between risk and returns. Given that disagreement is intrinsically unobservable, researchers often rely on proxies[9]. In line with most of the literature, we will use analysts forecasts. More precisely, we use as our proxy the dispersion in analyst forecasts of the Earnings Per Share (EPS) at the end of the current fiscal year, obtained via the S&P Capital IQ database.

While our first analysis will focus on the impact of stock-level dispersion of forecasts on returns, we describe the method we will use to construct a time series for a market-wide measure of disagreement. How do we average all the stock-level information to form a monthly data point? A first instinct would be to just take an equal-weighted or value-weighted average of all stock-level standard deviation of earnings forecasts (SDEFs), and to repeat this for all periods. What we do is close to this, except the weight we confer to each stock is based on its CAPM's beta. This method is similar in spirit to Yu (2011) and was also used in Hong and Sraer (2016).

[6] For instance, Chen et al. (2013) compares the period 1926-2010 to 1946-2010.
[7] In their work, they use this VAR specification as a benchmark with which to compare their methodology which proposes a direct estimation of cash flow news.
[8] See Welch and Goyal (2008).
[9] Other experimental methods are envisioned in Zanardo (2016).

Our estimates for market betas by following the literature and constructing beta portfolios. Each month, we use past weekly returns (with a minimum of 30 weeks and a maximum of 80 weeks) to regress the stock's return on the contemporaneous market return. We then sort stocks in 20 beta portfolios based on these pre-ranking betas. We compute the monthly equal-weighted returns on these portfolios. We then compute post-ranking betas by regressing each portfolio return on the market returns. These post-ranking betas are computed using the entire sample period, following Fama and French (1992).

Weighting our stock-level disagreement measures by beta is appealing because our analysis is mostly concerned with the disagreement component of a stock-dividend process that is related with the aggregate factor, and not with more idiosyncratic sources of disagreement. At the extreme, a stock with a beta of 0 would not be impacted at all by the aggregate factor, and its disagreement can only come from idiosyncratic disagreement.

This methodology gives us to the time-series of disagreement displayed in Figure 2.1.

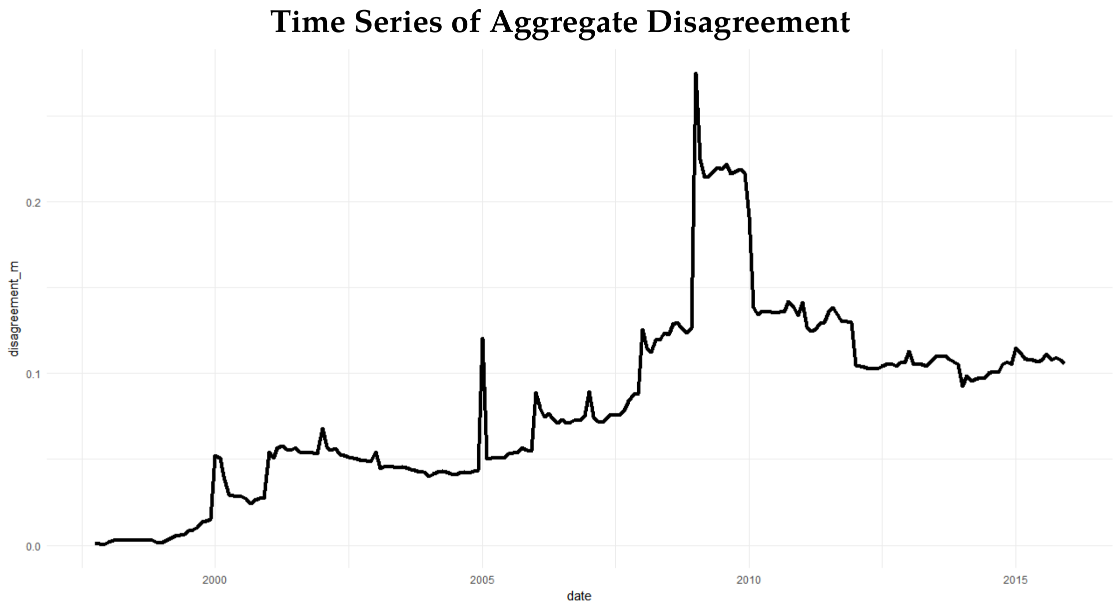

Figure 2.1: Time Series of Aggregate Disagreement
Sample period: 12/1996 to 12/2015. Sample: Stocks in the Capital IQ database, excluding stocks with price < $5. Each month, we calculate for each stock the standard deviation of analyst forecasts for the EPS, our measure of stock-level disagreement. We use portfolio post-ranking betas to weight each individual stock's dispersion of forecasts to obtain a monthly, aggregate disagreement measure.

We have chosen to restrict our sample to firms for which we have at least four analysts, and there are at least four data points on which to calculate the standard deviation of forecasts. This ensures that there is sufficient information in our dispersion measures, but might induce some bias in our results, due to the fact that the subgroup firms for which there is sufficient coverage might not be a random sample of the population.

2.2.4 Estimation of returns by portfolio

At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. We compute equal-weighted excess returns for each of the resulting 40 portfolios, 20 for cash flow betas and 20 for discount rate betas, over a period of 1, 3, 6, and 12 months. Table 2.1 displays summary statistics for our 20 portfolios based on cash flow and discount rate betas.

2.3 Results

2.3.1 Stock-level disagreement

Our first interest is to consider to what extent stock-level measures of disagreement impact the relationship between our decomposed measures of risk, cash flow news and discount rate news, and returns.

Figure 2.2 shows the average excess returns for our 40 cash flow and discount rate beta portfolios, with cash flow portfolios on the left-hand side, and discount rate portfolios on the right-hand side. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months (in rows) for stocks in the bottom quartile of the monthly distribution of stock-level dispersion of forecasts (in the blue circles) and stocks in the top quartile (in the red circles).

Some patterns emerge from visual inspection. First of all, for high and low stock-level SDEF stocks, and in accord with a trove of previous empirical results, we see that the relationship between excess returns and measures of risk, here cash flow and discount rate betas, does not appear to be positive. This is in agreement with the findings of Black (1972), or more recently of Frazzini and Pedersen (2014), who explain this by building a model with investors faced with funding constraints. We note, however, that our analysis leave out the middle half of our sample, each month, for which the stock-level SDEF lies either in the second of third quartile of the empirical distribution, and which might display other patterns.

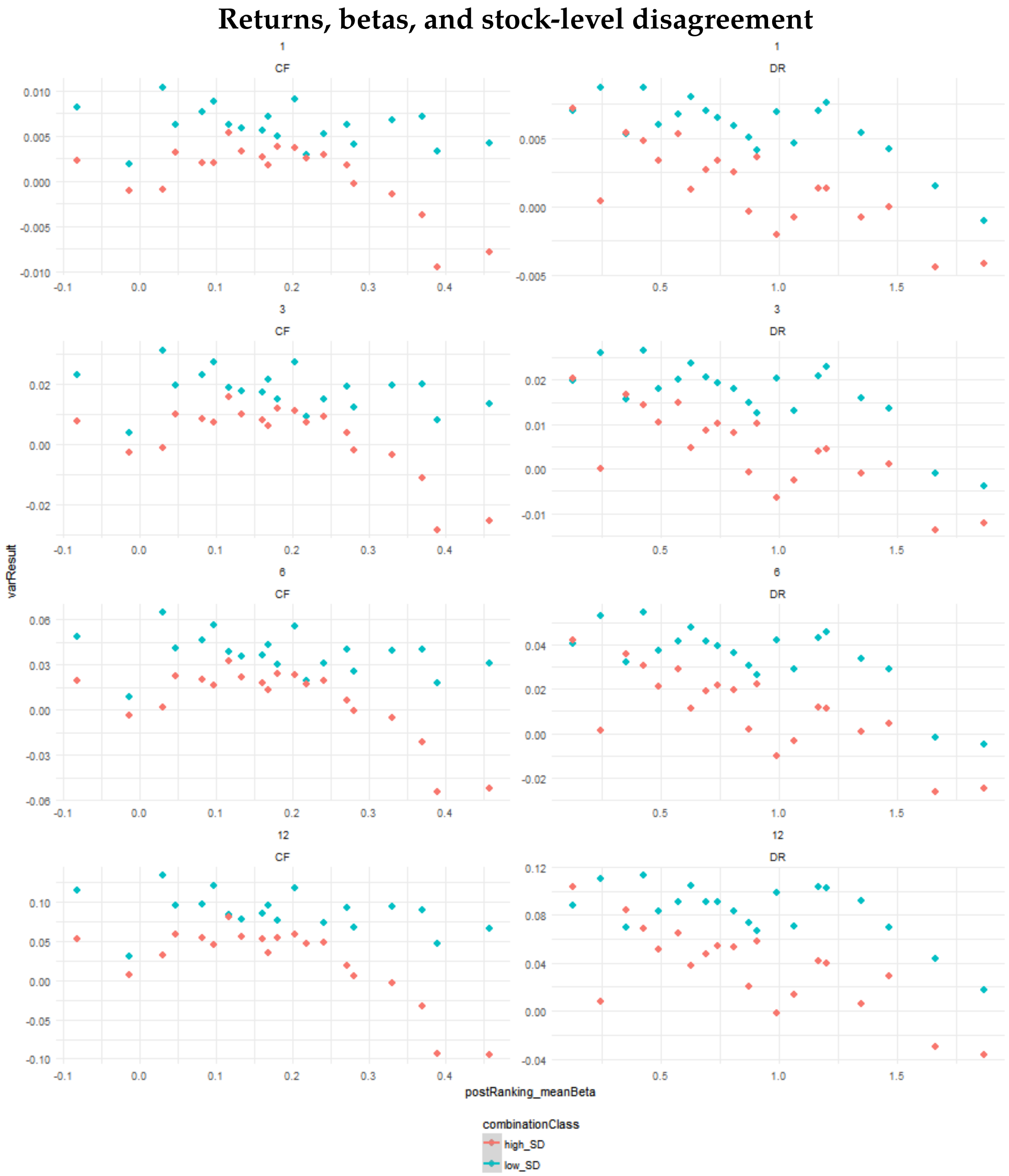

Figure 2.2: Returns, betas, and stock-level disagreement

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months for stocks in the bottom quartile of stock-level disagreement (blue circles) and months in the top quartile of stock-level disagreement (red circles).

Table 2.1: Summary Statistics for 20 beta-sorted portfolios

Sample: Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both cash flow betas and discount rate betas. We compute the full-sample beta of these 20 beta-sorted portfolios using the same market model.

Cash-flow betas	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
BetaEW	-0.11	-0.02	-0.01	0.02	0.04	0.05	0.07	0.08	0.10	0.11	0.13	0.15	0.17	0.18	0.20	0.23	0.25	0.28	0.32	0.38
BetaVW	-0.03	-0.03	-0.00	0.03	0.05	0.07	0.11	0.07	0.11	0.09	0.18	0.14	0.16	0.19	0.18	0.22	0.28	0.29	0.26	0.28
1-m return	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
12-m return	0.07	0.09	0.10	0.08	0.08	0.10	0.10	0.08	0.10	0.09	0.10	0.11	0.08	0.08	0.08	0.08	0.09	0.08	0.07	0.06
Stock Disag.	0.08	0.14	0.12	0.07	0.09	0.13	0.09	0.07	0.07	0.11	0.08	0.06	0.08	0.08	0.09	0.11	0.09	0.08	0.06	0.06
N Stocks	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93
Discount-rate betas	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
BetaEW	0.06	0.23	0.34	0.42	0.49	0.56	0.60	0.68	0.73	0.81	0.83	0.87	0.91	1.00	1.08	1.14	1.23	1.34	1.48	1.66
BetaVW	0.13	0.19	0.33	0.46	0.43	0.56	0.58	0.59	0.74	0.75	0.79	0.88	0.83	0.93	1.00	1.08	1.20	1.26	1.29	1.16
1-m return	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
12-m return	0.06	0.06	0.08	0.09	0.09	0.08	0.07	0.09	0.10	0.09	0.10	0.10	0.08	0.09	0.09	0.10	0.09	0.08	0.08	0.07
Stock Disag.	0.09	0.09	0.08	0.05	0.14	0.17	0.07	0.07	0.10	0.12	0.07	0.06	0.06	0.07	0.11	0.06	0.11	0.06	0.06	0.16
N Stocks	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93	93

2.3.2 Market-wide disagreement

An hypothesis we would like to investigate is whether our market-wide aggregate measure of disagreement can provide additional insights.

In Figure 2.3, we perform the same analysis that we used to obtain the graphs in Figure 2.2, but we add another layer to our analysis. We differentiate between the returns obtained in months in the lowest quartile of the disagreement time series, and months in the highest quartile. For each of these two sub-samples, as in our previous analysis, we distinguish between excess returns for stocks displaying low and high stock-level SDEF.

We thus obtain four different curves, for each of our separate configurations of time horizons (1, 3, 6 and 12 months), in rows, and type of beta, in columns, with cash flow betas portfolios on the left, and discount rate betas portfolios on the right. We observe that the differences in the shape of their return curves are more pronounced when we distinguish between states of market disagreement than between stock-level disagreement. The blue and purple curve denote the returns of high- and low- stock-level disagreement in *months of low market disagreement*, and they are nearly indistinguishable from each other. The red and green curves are the equivalent for *months of high market disagreement*. Again, we observe the same pattern, that is to say that their shape is roughly similar, even though we also note that it would seem that the spread is a bit higher than in low disagreement months.

Another way of putting this is that, while there are considerable differences in the patterns of risk and return, it seems that market-wide disagreement levels are a more important driver in shaping this relationship than stock-level disagreement.

What could explain the prevalence of our aggregate disagreement measure? A possible explanation can be found in Figures 2.4 to 2.6, in which we highlight the role played by aggregate disagreement on the relationship between stock-level disagreement on the one hand, and cash flow and discount rate betas on the other hand. In these figures, as before, we have divided our time series of aggregate disagreement into high aggregate-disagreement months (blue circles) and low-aggregate-disagreement months (red triangles), where high- (low-) aggregate disagreement months are defined as those in the top (bottom) quartiles of the in-sample distribution of aggregate disagreement. Then, for each of our 20 β-sorted portfolios, we plot the value-weighted average of the stock-level dispersion in analyst earnings forecasts against the post-ranking full sample β of the value-weighted portfolio. We do likewise for portfolios constructed on the basis of cash flow and discount rate betas.

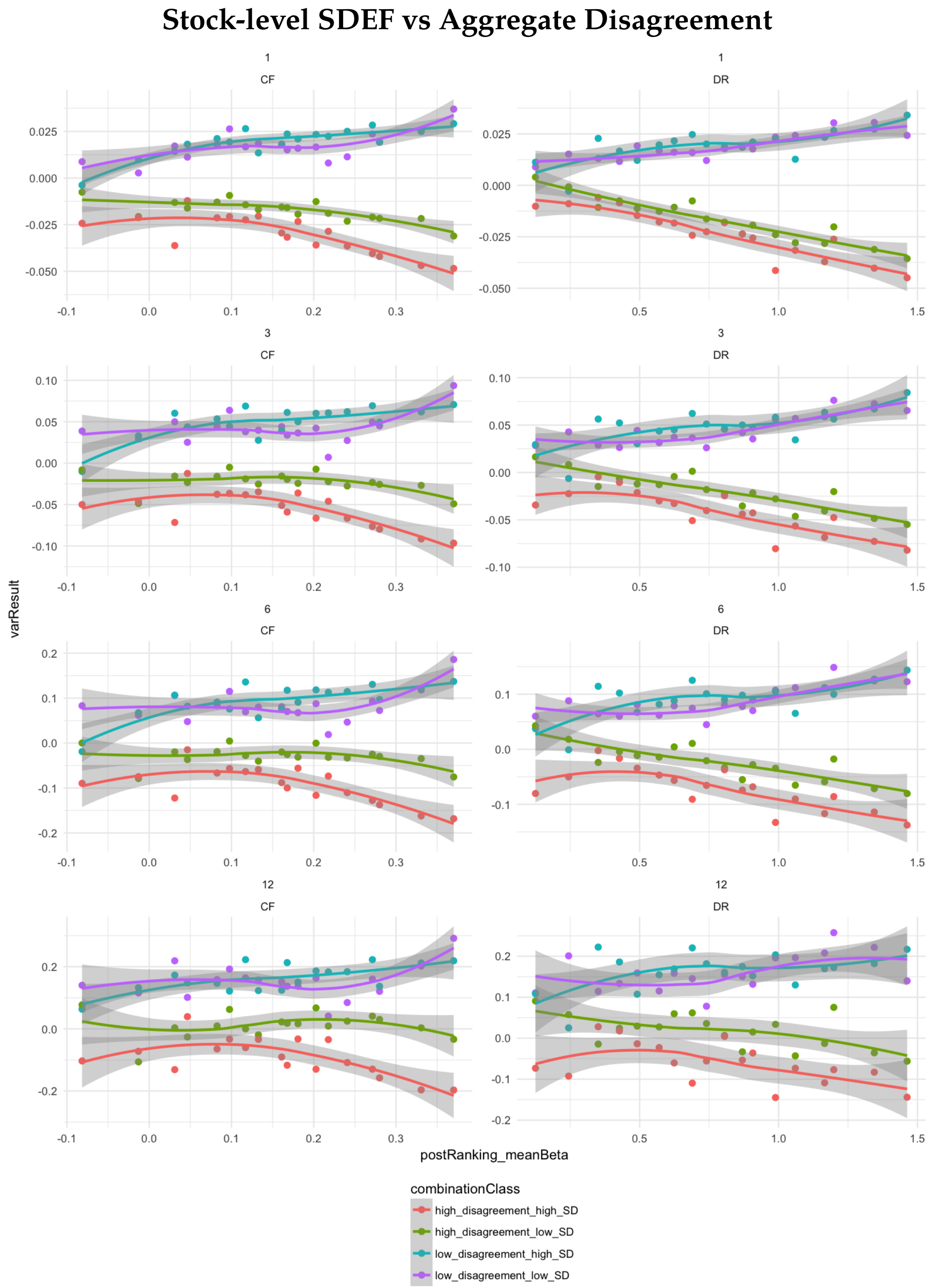

Figure 2.3: Stock-level SDEF vs Aggregate Disagreement

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months and split our sample both between months in the lowest and highest quartile of the disagreement distribution, and also between stocks comprising the lowest and highest quartile of the stock-level dispersion of EPS forecasts. Aggregate disagreement is the monthly β-weighted average of stock-level disagreement measures as the standard deviation of analyst forecasts for EPS. *Note:* Curves and shaded areas are smoothing splines provided to aid with series identification and pattern recognition, and should not be interpreted as carrying information with regards to level of statistical significance.

Another advantage of using a market-wide measure of risk it that it allows us not to be troubled by the issue of being able to separate, in the stock-level disagreement measures, which part is attributable to idiosyncratic factors vs. common factors, such as aggregate corporate profit levels. Anderson et al. (2009), for instance, show that in theory, individual disagreement matters only when this divergence of opinion is correlated with aggregate market sentiment [10].

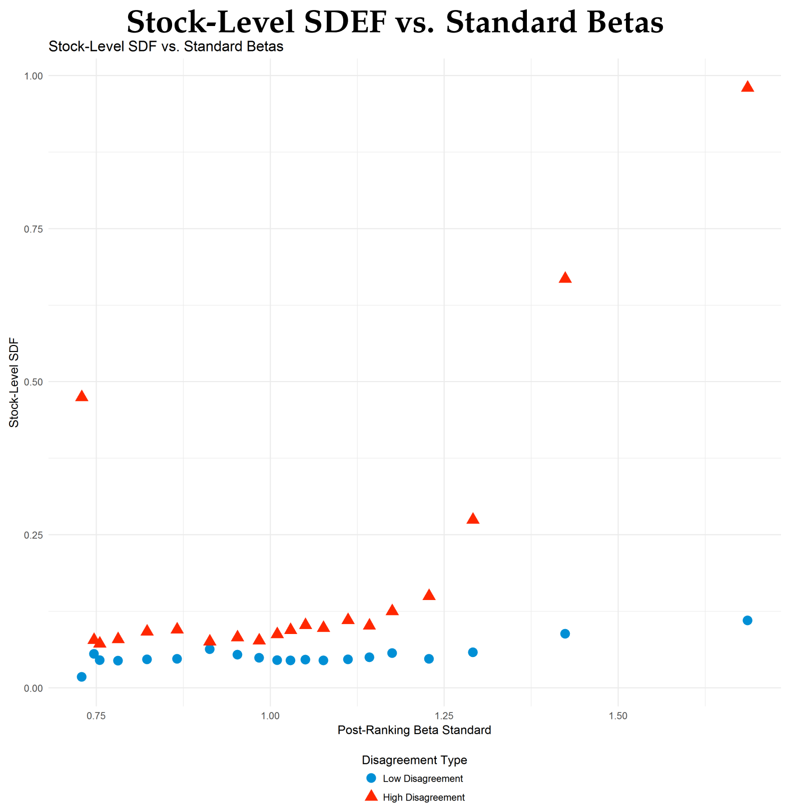

Figure 2.4: Stock-Level SDEF vs. Standard Betas
Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation standard betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for standard betas. The graph plots the equal-weighted average stock-level disagreement of stocks in 20 portfolios for months in the bottom 25% of aggregate disagreement (blue circles) and months in the top 25% of aggregate disagreement (red triangles).

We see that stock-level disagreement generally increases with β, and importantly that this relationship is markedly steeper in periods of high disagreement, denoted by red triangles. The trend is especially clear for standard and cash flow betas. We do note some discontinuities in the case of discount rate betas for medium to low values of beta, but the trend still points to an increasing relation-

[10] Even though in their case, they are interested in disagreement as it pertains to uncertainty, in its Knightian interpretation of an unknown unknown.

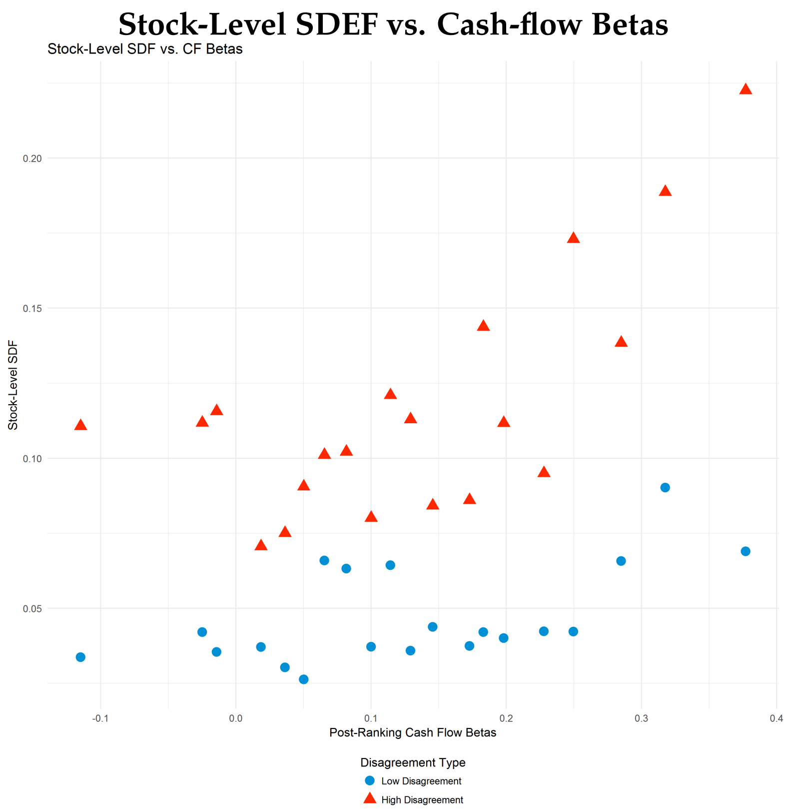

Figure 2.5: Stock-Level SDEF vs. Cash-flow Betas
Stocks in the Capital IQ database, excluding penny stocks (price < \$5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. The graph plots the equal-weighted average stock-level disagreement of stocks in 20 cash-flow portfolios for months in the bottom 25% of aggregate disagreement (blue circles) and months in the top 25% of aggregate disagreement (red triangles).

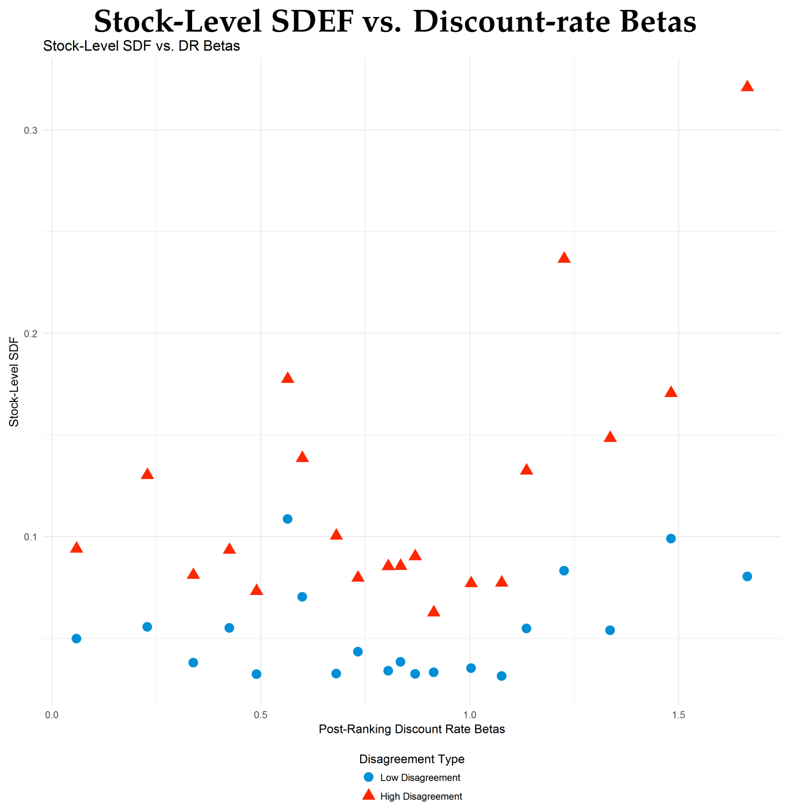

Figure 2.6: Stock-Level SDEF vs. Discount-rate Betas
Stocks in the Capital IQ database, excluding penny stocks (price < \$5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. The graph plots the equal-weighted average stock-level disagreement of stocks in 20 discount-rate portfolios for months in the bottom 25% of aggregate disagreement (blue circles) and months in the top 25% of aggregate disagreement (red triangles).

ship between stock-level dispersion of forecasts and mean betas. This observation also directly lends support to Miller (1977), in which divergence of opinion is expected to be higher for riskier securities.

In Tables 2.2 to 2.4, we propose another way to look into this. These tables aim to show the contrast in excess returns in the cases of respectively standard betas portfolios, cash flow, and discount rate portfolios. Panel A shows the difference between low- and high- stock-level disagreement stocks, for months with similar levels of aggregate disagreement. Panel B does the opposite, and shows the difference between the excess returns in months of low and high disagreement, for stocks with similar measures of dispersion of forecasts. The row difference is the square difference. For each sub-panel, we also provide the mean squared difference across all portfolios.

Our intention at this stage is to gain insight as to which measure of disagreement better explains the differences in returns. To do so, we draw attention to the measures of mean squared difference that are presented, in each table, for each of the four sub-panels. We are interested in both the difference between sub-panels *within* each panel, bet, and differences across panels.

In Table 2.2, we see in Panel A that the mean squared difference between stocks with high stock-level SDEF is similar in states of low and high disagreement, with values of 0.0014 and 0.0162 respectively. Similarly, in Panel B, we observe that the mean difference between states of low and high disagreement is similar in the sub-sample comprised of low stock-level SDEF stocks to the value for high-level SDEF stocks, with measures of 0.0166 and 0.016 respectively. At this stage, we do not see any trace of the pattern we are looking for.

The picture appears quite different for portfolios formed on decomposed betas, however. In Table 2.3, the table which presents the results for cash flow betas portfolios, we see that the mean squared differences we obtain in Panel B, of 0.0149 and 0.0372, are much higher than what we obtain in Panel A, i.e. 0.0024 and 0.0067. This leads us to think that the difference that matters the most is the one between disagreement *market states*, rather than the one between disagreement *at the stock level*.

Furthermore, we also see that the difference we do observe between low and high stock-level SDEF stocks is higher in states of high disagreement, with a mean difference of 0.0067 that is three times as high as the one in low disagreement, of 0.0024. This could point to the fact that, while the difference in stock-level disagreement can matter, it does so in a clearer manner in periods of high disagreement.

Table 2.4, as expected, shows very similar results to the ones we observed in Table 2.3. We observe the same pattern that the mean squared differences in returns are higher between market disagreement states, holding stock-level disagreement constant, than vice-versa. And also in a similar fashion, it's in high disagreement months that the difference in returns is higher between low and high stock-level SDEF stocks.

In Figure 2.7, we represent the association between our decomposed betas and returns in months of low and high aggregate disagreement.

Compared with Figure 2.2, the relationships are more marked. Importantly, the range we obtain in values for excess returns between low and high disagreement is much higher than when comparing low and high stock-level SDEF, a result which is consistent with the results obtained in Tables 2.2 to 2.4.

Clearer patterns appear this time around. Striking differences, underlined by consistent patterns, appear both in the distinction between cash flow and discount rate betas, and also in the distinction between periods of low agreement and periods of high disagreement.

An upward relationship between a measure of risk and returns appears in only one configuration, when considering the relationship between cash flow betas and returns in periods of low disagreement. In this case, the curve displays a cubic aspect, with a slope more pronounced for low and high values, and nearly flat for medium values of cash flow betas.

In periods of high disagreement, the relationship between cash flow betas and returns is comparatively much flatter, displaying a slightly inverted-U shape.

With regards to discount rate betas, in periods of high disagreement, the slope is markedly negative, with a small bump for low betas. In periods of low disagreement, we see an inverted U-shape pattern that is highly reminiscent of the pattern observed in Hong and Sraer (2016), i.e an upward slope, until a certain value, where a "kick" is observed, and the relationship inverts, and displays a downward slope. Such a result also agrees with Baker et al. (2011) who find that the cumulative performance of stocks is actually declining with beta.

These results are consistent with the Miller (1977) interpretation that in the presence of some restrictions to the shorting abilities of investors, when there is some level of disagreement among market participants, pessimists are shut off the market, conferring more influence to the price signal carried by optimistic investors [11]. This is also consistent with Diether et al. (2002), even though in their case, they consider stock-level dispersion of forecasts.

We suggest the following interpretation. In periods of high disagreement, the relationship between returns and measures of risk breaks down. Both for cash

[11] Also sometimes referred to as sentiment investors.

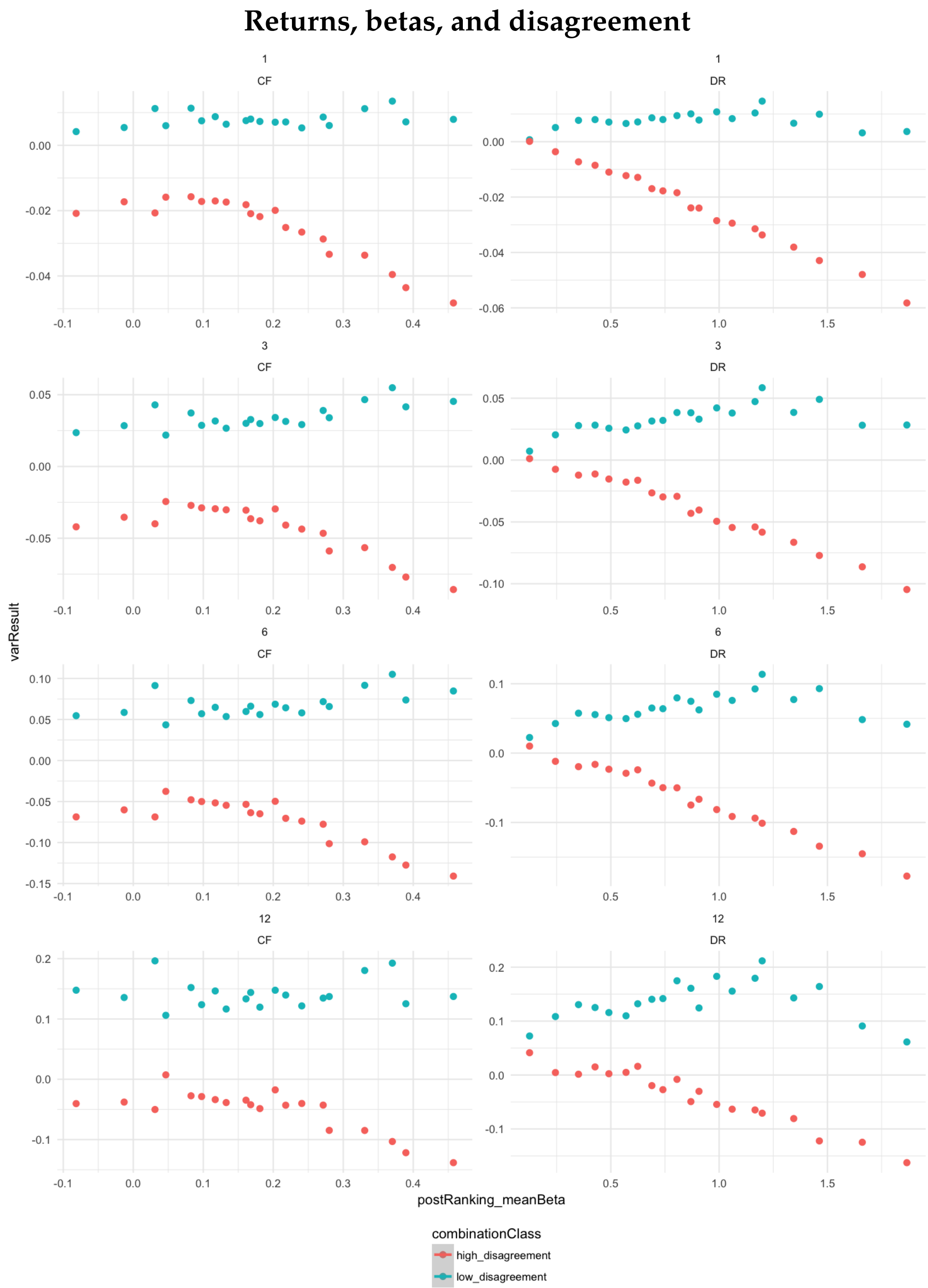

Figure 2.7: Returns, betas, and disagreement

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months for months in the bottom quartile of aggregate disagreement (blue circles) and months in the top quartile of aggregate disagreement (red circles). Aggregate disagreement is the monthly β-weighted average of stock-level disagreement measures as the standard deviation of analyst forecasts for EPS.

Table 2.2: Stock-Level Dispersion of Forecasts vs. Aggregate Market Disagreement

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation standard betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The table shows differences in excess returns across two-way splits of the sample, one in the time series of aggregate market disagreement, and the other in the individual stocks, in levels of stock-level standard deviation of earnings forecasts. In Panel A, for each standard portfolio, we hold constant the level of market disagreement in each sub-panel, and compare average excess returns for stocks with low and high levels of stock-level SDEF. In Panel B, the two sub-panels correspond to two sub-samples of different SDEF stocks, for which we compare the average excess returns in low and high aggregate disagreement states. The line "Difference" corresponds to the squared difference in excess returns.

Standard Portfolio	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
PANEL A : WITHIN MARKET DISAGREEMENT STATES, THE IMPACT OF STOCK-LEVEL STANDARD DEVIATION OF FORECASTS																				
Low Disagreement – Mean Difference : 0.0014																				
Low SL-SDEF	0.1985	0.0820	0.0262	0.0337	0.0495	0.0505	0.0452	0.0397	0.0341	0.0285	0.0449	0.0553	0.0507	0.0461	0.0422	0.0388	0.0345	0.0528	0.0031	-0.0131
High SL-SDEF	0.3278	0.0684	0.0868	0.0766	0.0848	0.0742	0.0569	0.0226	0.0390	0.0369	0.0109	0.0440	0.0534	0.0491	0.0167	0.0655	0.0647	0.0275	0.0006	-0.0100
Difference	0.0167	0.0002	0.0037	0.0018	0.0012	0.0006	0.0001	0.0003	0.0000	0.0001	0.0012	0.0001	0.0000	0.0000	0.0007	0.0007	0.0009	0.0006	0.0000	0.0000
High Disagreement – Mean Difference : 0.0162																				
Low SL-SDEF	-0.1045	0.0137	0.0116	0.0221	0.0001	0.0265	0.0209	0.0281	0.0293	0.0321	0.0243	0.0284	0.0504	0.0285	0.0255	0.0288	0.0427	0.0413	0.0400	-0.4898
High SL-SDEF	-0.0670	-0.0431	-0.0080	-0.0213	-0.0328	-0.0466	-0.0356	-0.0535	-0.0602	-0.0550	-0.0435	-0.0398	-0.0470	-0.0516	-0.0429	-0.0364	-0.0570	-0.0464	-0.0850	-0.0231
Difference	0.0014	0.0032	0.0004	0.0019	0.0011	0.0053	0.0032	0.0067	0.0080	0.0076	0.0046	0.0047	0.0095	0.0064	0.0047	0.0043	0.0099	0.0077	0.0156	0.2178
PANEL B : CONSIDERING THE RETURNS OF STOCK WITH SIMILAR SDEF, THE IMPACT OF MARKET DISAGREEMENT STATES																				
Low SL-SDEF Stocks – Mean Difference : 0.0166																				
Low Disagreement	0.1985	0.0820	0.0262	0.0337	0.0495	0.0505	0.0452	0.0397	0.0341	0.0285	0.0449	0.0553	0.0507	0.0461	0.0422	0.0388	0.0345	0.0528	0.0031	-0.0131
High Disagreement	-0.1045	0.0137	0.0116	0.0221	0.0001	0.0265	0.0209	0.0281	0.0293	0.0321	0.0243	0.0284	0.0504	0.0285	0.0255	0.0288	0.0427	0.0413	0.0400	-0.4898
Difference	0.0918	0.0047	0.0002	0.0001	0.0024	0.0006	0.0006	0.0001	0.0000	0.0000	0.0004	0.0007	0.0000	0.0003	0.0003	0.0001	0.0001	0.0001	0.0014	0.2272
High SL-SDEF Stocks – Mean Difference : 0.016																				
Low Disagreement	0.3278	0.0684	0.0868	0.0766	0.0848	0.0742	0.0569	0.0226	0.0390	0.0369	0.0109	0.0440	0.0534	0.0491	0.0167	0.0655	0.0647	0.0275	0.0006	-0.0100
High Disagreement	-0.0670	-0.0431	-0.0080	-0.0213	-0.0328	-0.0466	-0.0356	-0.0535	-0.0602	-0.0550	-0.0435	-0.0398	-0.0470	-0.0516	-0.0429	-0.0364	-0.0570	-0.0464	-0.0850	-0.0231
Difference	0.1559	0.0124	0.0090	0.0096	0.0138	0.0146	0.0086	0.0058	0.0098	0.0084	0.0030	0.0070	0.0101	0.0101	0.0036	0.0104	0.0148	0.0055	0.0073	0.0002

Table 2.3: Stock-Level Dispersion of Forecasts vs. Aggregate Market Disagreement, CF Portfolios

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < \$5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation cash flow and discount rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The table shows differences in excess returns across two-way splits of the sample, one in the time series of aggregate market disagreement, and the other in the individual stocks, in levels of stock-level standard deviation of earnings forecasts. In Panel A, for each cash flow beta portfolio, we hold constant the level of market disagreement in each sub-panel, and compare average excess returns for stocks with low and high levels of stock-level SDEF. In Panel B, the two sub-panels correspond to two sub-samples of different SDEF stocks, for which we compare the average excess returns in low and high aggregate disagreement states. The line "Difference" corresponds to the squared difference in excess returns.

CF Portfolio	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
PANEL A : WITHIN MARKET DISAGREEMENT STATES, THE IMPACT OF STOCK-LEVEL STANDARD DEVIATION OF FORECASTS																				
Low Disagreement – Mean Difference : 0.0024																				
Low SL-SDEF	0.0707	0.0505	0.0963	0.0383	0.0717	0.0971	0.0650	0.0669	0.0729	0.0575	0.0570	0.0740	0.0082	0.0343	0.0806	0.0560	0.0902	0.1423	0.1118	0.1104
High SL-SDEF	0.0048	0.0594	0.0783	0.0754	0.0880	0.0642	0.1135	0.0600	0.0619	0.0975	0.0729	0.0907	0.0910	0.0979	0.1207	0.0700	0.1015	0.1111	-0.0027	0.0167
Difference	0.0043	0.0001	0.0003	0.0014	0.0003	0.0011	0.0024	0.0000	0.0001	0.0016	0.0003	0.0003	0.0069	0.0040	0.0016	0.0002	0.0001	0.0010	0.0131	0.0088
High Disagreement – Mean Difference : 0.0067																				
Low SL-SDEF	-0.0179	-0.0703	-0.0152	-0.0390	-0.0207	-0.0003	-0.0298	-0.0428	-0.0206	-0.0304	-0.0360	-0.0029	-0.0363	-0.0468	-0.0362	-0.0306	-0.0490	-0.0964	-0.1026	-0.0761
High SL-SDEF	-0.1030	-0.0985	-0.1392	-0.0370	-0.0936	-0.0753	-0.0691	-0.0646	-0.0899	-0.1049	-0.0541	-0.1145	-0.0821	-0.1142	-0.1344	-0.1536	-0.1575	-0.1794	-0.1767	-0.2130
Difference	0.0072	0.0008	0.0154	0.0000	0.0053	0.0056	0.0015	0.0005	0.0048	0.0056	0.0003	0.0125	0.0021	0.0045	0.0096	0.0151	0.0118	0.0069	0.0055	0.0187
PANEL B : CONSIDERING THE RETURNS OF STOCK WITH SIMILAR SDEF, THE IMPACT OF MARKET DISAGREEMENT STATES																				
Low SL-SDEF Stocks – Mean Difference : 0.0149																				
Low Disagreement	0.0707	0.0505	0.0963	0.0383	0.0717	0.0971	0.0650	0.0669	0.0729	0.0575	0.0570	0.0740	0.0082	0.0343	0.0806	0.0560	0.0902	0.1423	0.1118	0.1104
High Disagreement	-0.0179	-0.0703	-0.0152	-0.0390	-0.0207	-0.0003	-0.0298	-0.0428	-0.0206	-0.0304	-0.0360	-0.0029	-0.0363	-0.0468	-0.0362	-0.0306	-0.0490	-0.0964	-0.1026	-0.0761
Difference	0.0078	0.0146	0.0124	0.0060	0.0085	0.0095	0.0090	0.0120	0.0087	0.0077	0.0086	0.0059	0.0020	0.0066	0.0136	0.0075	0.0194	0.0570	0.0460	0.0348
High SL-SDEF Stocks – Mean Difference : 0.0372																				
Low Disagreement	0.0048	0.0594	0.0783	0.0754	0.0880	0.0642	0.1135	0.0600	0.0619	0.0975	0.0729	0.0907	0.0910	0.0979	0.1207	0.0700	0.1015	0.1111	-0.0027	0.0167
High Disagreement	-0.1030	-0.0985	-0.1392	-0.0370	-0.0936	-0.0753	-0.0691	-0.0646	-0.0899	-0.1049	-0.0541	-0.1145	-0.0821	-0.1142	-0.1344	-0.1536	-0.1575	-0.1794	-0.1767	-0.2130
Difference	0.0116	0.0249	0.0473	0.0126	0.0330	0.0195	0.0333	0.0155	0.0230	0.0410	0.0161	0.0421	0.0300	0.0450	0.0651	0.0500	0.0671	0.0844	0.0303	0.0528

Table 2.4: Stock-Level Dispersion of Forecasts vs. Aggregate Market Disagreement, DR Portfolios

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation cash flow and discount rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The table shows differences in excess returns across two-way splits of the sample, one in the time series of aggregate market disagreement, and the other in the individual stocks, in levels of stock-level standard deviation of earnings forecasts. In Panel A, for each discount rate beta portfolio, we hold constant the level of market disagreement in each sub-panel, and compare average excess returns for stocks with low and high levels of stock-level SDEF. In Panel B, the two sub-panels correspond to two sub-samples of different SDEF stocks, for which we compare the average excess returns in low and high aggregate disagreement states. The line "Difference" corresponds to the squared difference in excess returns.

DR Portfolio	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Panel A : Within market disagreement states, the impact of stock-level standard deviation of forecasts																				
Low Disagreement – Mean Difference : 0.0019																				
Low SL-SDEF	0.0543	0.0850	0.0462	0.0562	0.0709	0.0493	0.0680	0.0641	0.0358	0.0706	0.0626	0.0536	0.0951	0.0957	0.0943	0.1226	0.1053	0.0871	-0.0541	0.0754
High SL-SDEF	0.0331	0.0072	0.1040	0.0921	0.0541	0.0749	0.0849	0.1101	0.0807	0.0783	0.0883	0.0697	0.0917	0.0559	0.0836	0.0839	0.0999	0.1257	0.0659	0.0301
Difference	0.0004	0.0061	0.0033	0.0013	0.0003	0.0007	0.0003	0.0021	0.0020	0.0001	0.0007	0.0003	0.0000	0.0016	0.0001	0.0015	0.0000	0.0015	0.0144	0.0021
High Disagreement – Mean Difference : 0.004																				
Low SL-SDEF	0.0400	0.0183	-0.0166	0.0033	-0.0103	-0.0156	0.0001	0.0012	-0.0274	-0.0373	-0.0590	-0.0427	-0.0430	-0.0638	-0.0610	-0.0553	-0.0865	-0.0822	-0.0917	-0.1398
High SL-SDEF	-0.0656	-0.0394	-0.0175	-0.0254	-0.0308	-0.0470	-0.0731	-0.0994	-0.0728	-0.0504	-0.0937	-0.0747	-0.1331	-0.1128	-0.1267	-0.1125	-0.1372	-0.1597	-0.1980	-0.2113
Difference	0.0112	0.0033	0.0000	0.0008	0.0004	0.0010	0.0054	0.0101	0.0021	0.0002	0.0012	0.0010	0.0081	0.0024	0.0043	0.0033	0.0026	0.0060	0.0113	0.0051
Panel B : Considering the returns of stock with similar SDEF, the impact of market disagreement states																				
Low SL-SDEF Stocks – Mean Difference : 0.0142																				
Low Disagreement	0.0543	0.0850	0.0462	0.0562	0.0709	0.0493	0.0680	0.0641	0.0358	0.0706	0.0626	0.0536	0.0951	0.0957	0.0943	0.1226	0.1053	0.0871	-0.0541	0.0754
High Disagreement	0.0400	0.0183	-0.0166	0.0033	-0.0103	-0.0156	0.0001	0.0012	-0.0274	-0.0373	-0.0590	-0.0427	-0.0430	-0.0638	-0.0610	-0.0553	-0.0865	-0.0822	-0.0917	-0.1398
Difference	0.0002	0.0044	0.0039	0.0028	0.0066	0.0042	0.0046	0.0040	0.0040	0.0116	0.0148	0.0093	0.0191	0.0254	0.0241	0.0316	0.0368	0.0287	0.0014	0.0463
High SL-SDEF Stocks – Mean Difference : 0.0327																				
Low Disagreement	0.0331	0.0072	0.1040	0.0921	0.0541	0.0749	0.0849	0.1101	0.0807	0.0783	0.0883	0.0697	0.0917	0.0559	0.0836	0.0839	0.0999	0.1257	0.0659	0.0301
High Disagreement	-0.0656	-0.0394	-0.0175	-0.0254	-0.0308	-0.0470	-0.0731	-0.0994	-0.0728	-0.0504	-0.0937	-0.0747	-0.1331	-0.1128	-0.1267	-0.1125	-0.1372	-0.1597	-0.1980	-0.2113
Difference	0.0097	0.0022	0.0148	0.0138	0.0072	0.0149	0.0250	0.0439	0.0236	0.0166	0.0331	0.0209	0.0505	0.0285	0.0442	0.0386	0.0562	0.0815	0.0696	0.0583

flow and discount rate betas, we do not observe that higher risk assets command a higher return. This is even more pronounced for discount rate betas.

In states of low disagreement, we see that cash flow betas reflect the high risk premium theory predicts they should have, as derived for instance in the discussion in Campbell and Vuolteenaho (2004). Indeed, the compensation to the investor of the higher risk that these stocks represents is found empirically in higher returns.

High discount rate betas stocks, which thus carry a higher "good beta" by the distinction established by Campbell and Vuolteenaho (2004) (because they carry a lower theoretical risk premium than their cash flow counterparts), seem to be acting as a sort of "safe heaven" for investors, and even more so in periods of high disagreement. Lower returns for high discount rate betas stocks could be explained by the fact that such assets are the object of a greater demand in high-disagreement times. In periods of low disagreement, however, it seems there is a "threshold" above which this effect starts to be manifest.

At this stage, we point out that that this analysis has been carried out using other quantiles as "low" and "high" breakpoints in our disagreement time series. There is indeed no theoretically motivated argument that would incite us to prefer a "lowest-quartile vs. highest-quartile" approach over, for instance, another split based on thirds, or any other number. Our results, available upon request, are quite robust to moderate modifications in the break points, but while they do not affect our results extensively, it is inevitable that larger departures from our specifications have an impact. This is even more pronounced given that our database is rather short with respects to analyst's forecasts. More extensive robustness checks revolving around the disagreement time series follow in Section 2.3.4.

2.3.3 Robustness check – Impact of the decomposition of betas

But a fair question at this stage would be: does decomposing the betas in their cash flow and discount rate components bring something to our analysis? Do we need to distinguish between these two components to gain more insight in the influence of disagreement on the risk-return relationship?

To answer this, we take a look at our 20 portfolios based on standard betas. For each of these portfolios, we compute the average return during low disagreement months (blue dots) and high disagreement months (red dots). We perform this analysis for four different time horizons: 1, 3, 6, and 12 months.

In Figure 2.8, we see that it is difficult to observe any real clear pattern, except for the fact that, as expected, returns appear to be higher in low disagreement months, across all portfolios. No patterns are distinguishable in any of the curves.

2.3.4 Robustness check – Definition of disagreement months

A sensitive aspect of our methodology revolves around the market-wide measure of aggregate disagreement. It is crucial in the sense that it allows us to discern between months characterized by high and low level of disagreement.

Our main approach is to follow Hong and Sraer (2016) and use the raw time series to establish quantiles in the observed monthly values, and then to attribute, on the basis of quantile breakpoints, months in low and high categories.

Such a method is by no means the only way to obtain a distinction between low and high disagreement states. First of all, it might make sense to consider constraining the decision rule such that, at each month, it is only able to use information available to market participants at that time. Such a restriction would prove particularly meaningful if one would be willing to consider that the findings might be explained by behavioural elements, and that those behavioural elements involve agents making a judgment with respect to the current state of the environment, in this case, the current level of disagreement.

These methods are often grouped under the vocable "change detection", and are the subject of particular attention to practitioners in the climate sciences, medicine or biology. See Aminikhanghahi and Cook (2017) for a recent review of change detection techniques.

Choosing between online methods (using only information at the chosen period to characterize the period) or offline ones (using information in the whole time series) seems essentially contingent on one's interpretation of the underlying processes. Our argumentation mostly follows the argument put forward by Miller (1977), in which some agents are not able to carry their price signal to the market because of limits of arbitrage in cases of high dispersion of beliefs. This happens whether the agent has any opinion regarding the level of disagreement in the market or not, and therefore, it might seem more appropriate to categorize that level of disagreement with full information rather than time-constrained information.

We thus choose not to consider online algorithms in this situation. To ensure our results are robust to alternative methods of distinguishing between low and high disagreement months, we propose to redo our analysis, but after detrending our disagreement measure using a 2-year moving average. Figure 2.9 shows the resulting time series on the right-hand side. We see that the rising trend has been correctly filtered out of our series.

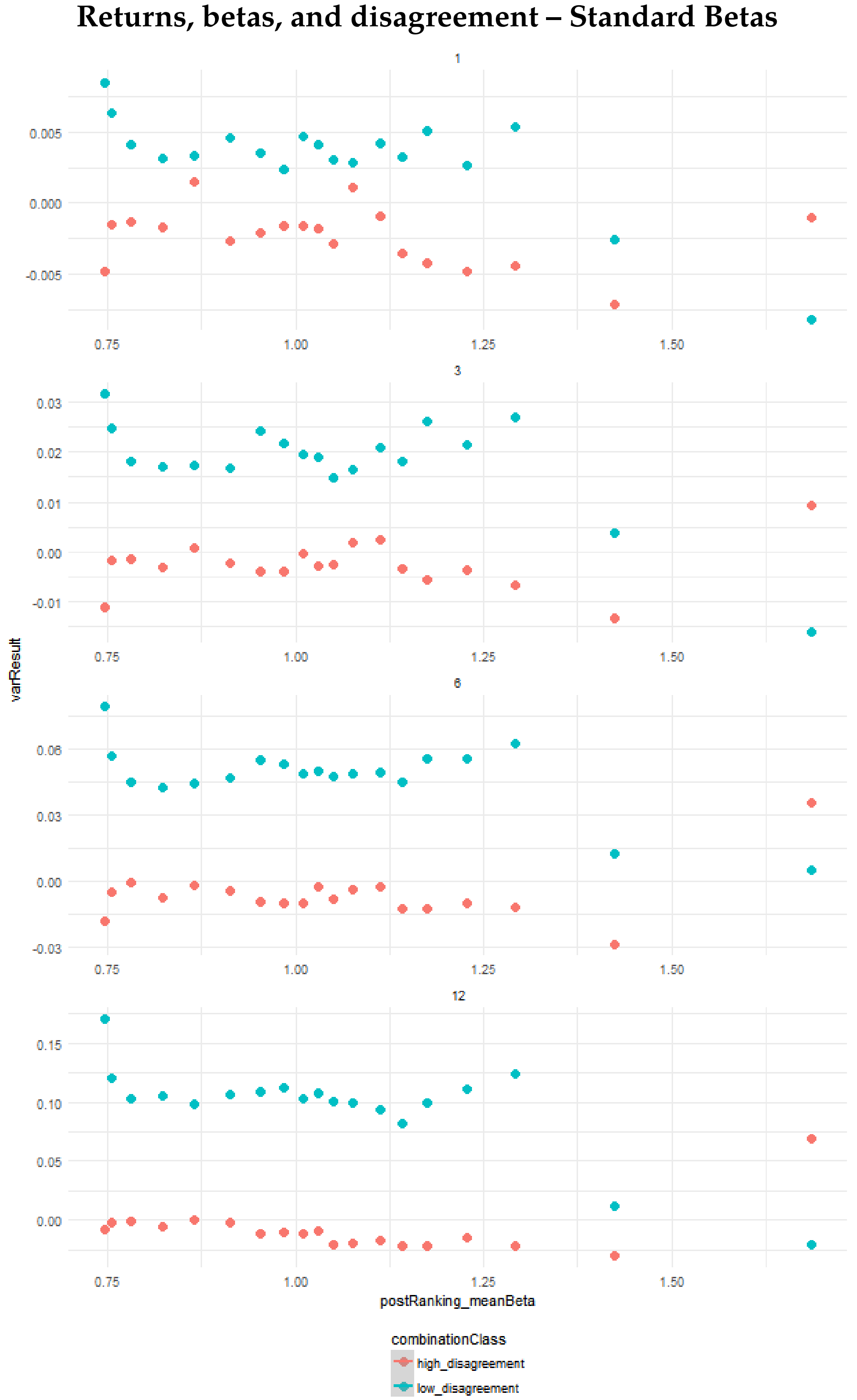

Figure 2.8: Returns, betas, and disagreement – Standard Betas
Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < \$5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Pre-formation Standard betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months for months in the bottom quartile of aggregate disagreement (blue circles) and months in the top quartile of aggregate disagreement (red circles). Aggregate disagreement is the monthly β-weighted average of stock-level disagreement measures as the standard deviation of analyst forecasts for EPS.

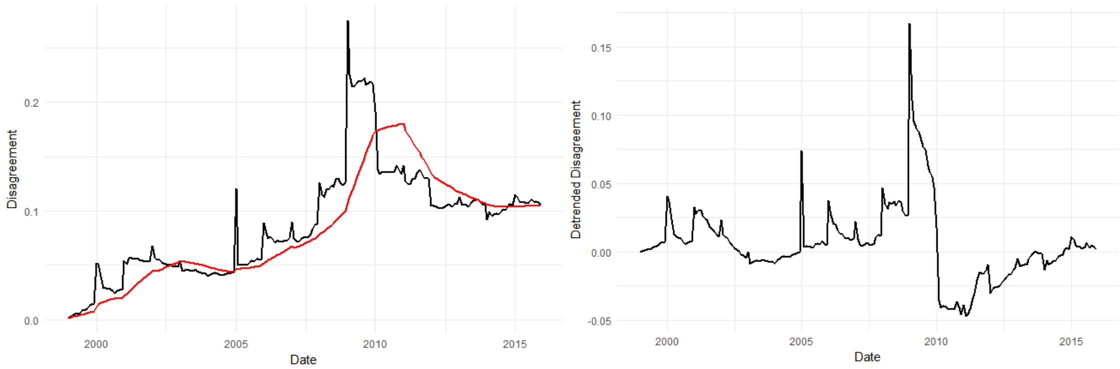

Figure 2.9: Detrending disagreement using moving averages

Sample period: 12/1996 to 12/2015. Sample: Stocks in the Capital IQ database, excluding stocks with price < $5. Each month, we calculate for each stock the standard deviation of analyst forecasts for the EPS, our measure of stock-level disagreement. We use portfolio post-ranking betas to weight each individual stock's dispersion of forecasts to obtain a monthly, aggregate disagreement measure. On the left-hand side, in black, the raw time series ; in red, the moving average using the past 2 years. On the right-hand side, the detrended resulting time series.

Here, rather than quartiles, we choose to split our resulting time series along the median, in a manner similar to Baker and Wurgler (2006). We see that periods of high and low disagreements are more spread out across our entire time series, with higher values appearing at the beginning, and low values in the early 2010's.

Figure 2.10 shows the average returns for our 20 beta-sorted portfolios. We observe that the patterns we identified in Figure 2.7 are preserved with this new definition of high and low disagreement months. No sizable distinction is to be noted, and the crux of our previous analysis still stands. There are some variations in the levels, for instance at the 12-month horizon, in high disagreement months, both for cash flow and discount rate beta portfolios, where we observe in this case more extreme negative values. Another possible deviation is the fact that the two-piece pattern observed for cash flow beta portfolios in high disagreement months is less marked.

We have investigated the sensitivity of these results to the choice of other quantiles for splitting the disagreement time series (ranging from the quartiles as in Hong and Sraer (2016) to the median as in Baker and Wurgler (2006)). While some deviations are bound to happen under such modifications, no significant pattern is modified. Results are available upon request. Even though detrending the time series using a moving average allows us to get rid of the trend that might bias our results, another critique that can be leveraged is that our results are excessively driven by the impact of a few months in our sample. Whether this should be considered a limitation or a feature of the analysis is, according to us,

Returns, betas, and detrended disagreement – 2-year moving average

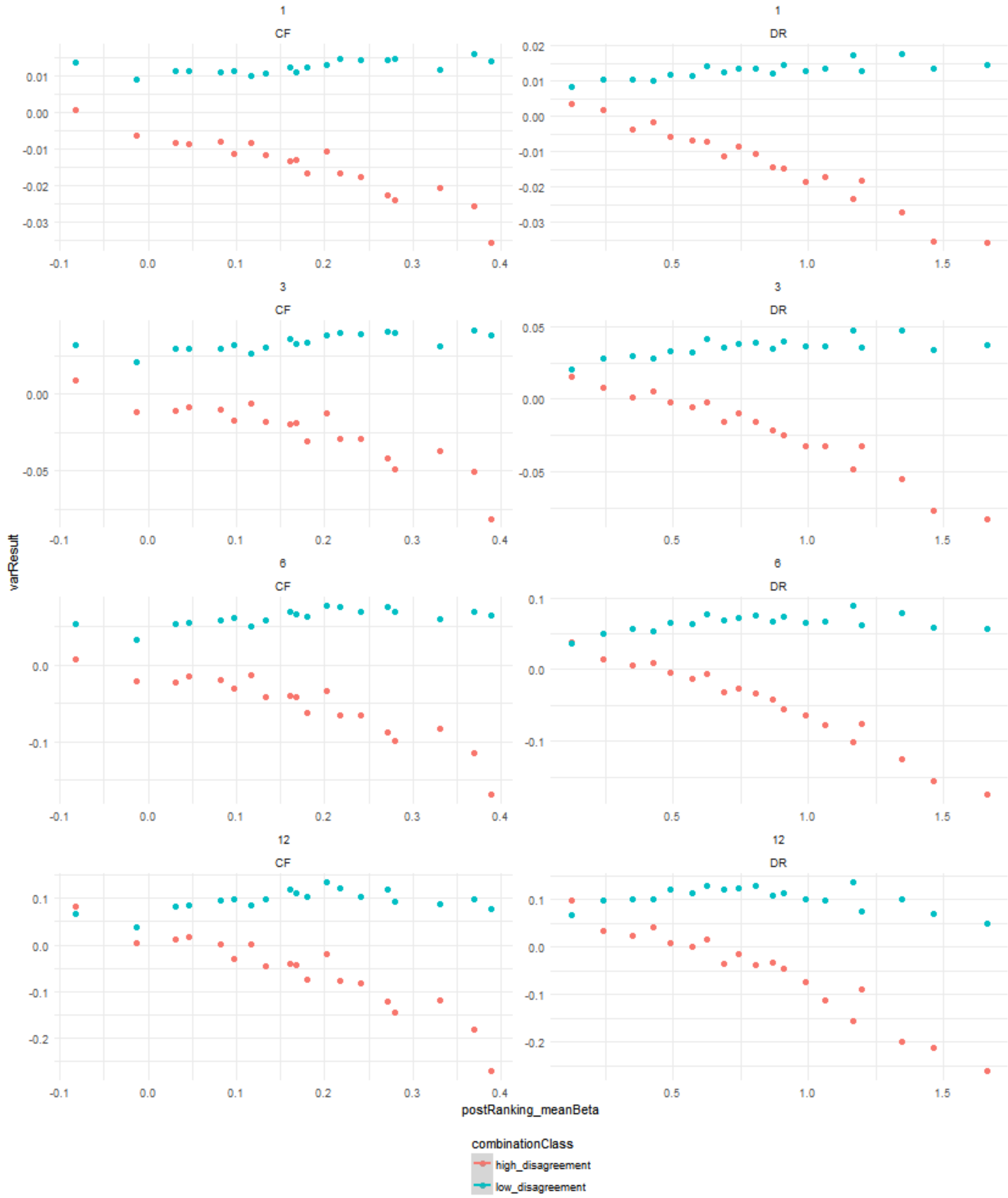

Figure 2.10: Returns, betas, and detrended disagreement – 2-year moving average
Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months for months in the bottom quartile of aggregate disagreement (blue circles) and months in the top quartile of aggregate disagreement (red circles). Aggregate disagreement is the monthly β-weighted average of stock-level disagreement measures as the standard deviation of analyst forecasts for EPS, which has been detrended by the 2-year moving average.

open to debate, as one might argue that it is precisely our intention to capture the impact of these particular time periods.

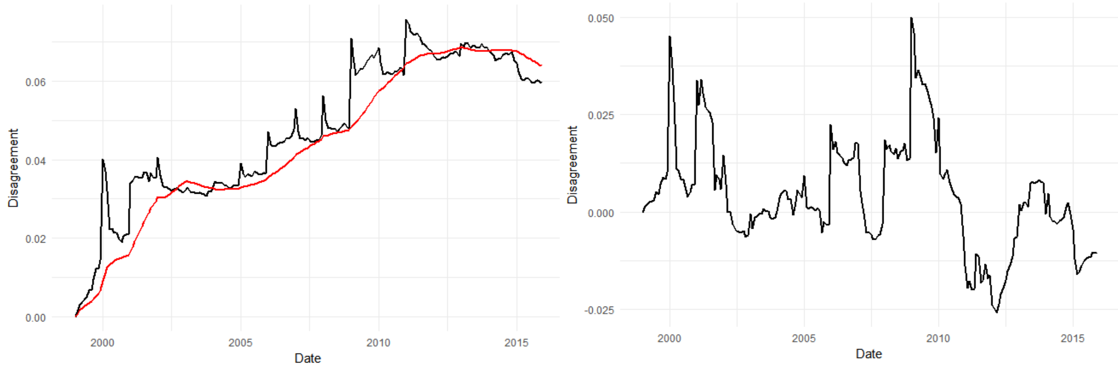

Figure 2.11: Detrending disagreement using winsorization and moving averages

Sample period: 12/1996 to 12/2015. Sample: Stocks in the Capital IQ database, excluding stocks with price < $5. Each month, we calculate for each stock the standard deviation of analyst forecasts for the EPS, our measure of stock-level disagreement. We use portfolio post-ranking betas to weight each individual stock's dispersion of forecasts to obtain a monthly, aggregate disagreement measure. On the left-hand side, in black, the time series winsorized at the 0.1% level ; in red, the moving average using the past 2 years. On the right-hand side, the detrended resulting time series.

That being said, it might be interesting to gain more confidence in our methodology, and investigate to which extent some extreme months are driving our results. We thus propose to winsorize the levels of our time series of disagreement at the 0.1% level, which has the effect of "flattening" our curve. The resulting series corresponds to the black curve on the left-hand side of Figure 2.11 as we can see in Figure 2.11[12].

The resulting time series displays a trend that is even more marked than our non-winsorized time series. In this situation, choosing quantiles to distinguish low and high disagreement months will amount to simply compare the later months to the earlier months. To circumvent this, we again choose to detrend this series by a 2-year moving average, which corresponds to the red curve on the left-hand side of Figure 2.11. The result, on the right-hand side, shows that this treatment has clearly removed both the trend and the importance of the extreme months, but to such an extent that we cannot exclude that some modicum of meaningful information has been lost in the process.

Again, we split our time series across the median, with months in the bottom (upper) half of the distribution denoting low (high) disagreement months. The

[12] Winsorization is a widely adopted practice in empirical finance, often used to (crudely) remove outliers in variables, see for instance Stoll et al. (2003); Baker and Wurgler (2006); Fama and French (2008); Yu (2011); Chen et al. (2013).

returns obtained for our each of our 20 cash flow and discount rate beta portfolios are in Figure 2.12. This time there are some noticeable changes in the patterns we observed before. What might not be easily visible at the naked eye, but is of decisive importance, is the fact that the range in returns are much tighter in this configuration, especially at the 1, 3, and 6-months horizons. A rough estimate is that the range has been compressed three-fold.

This is not surprising given that our manipulation of the disagreement time series delivers a pattern of high and low disagreement months that is much more noisy. What we do still observe are the lower returns, both for cash flow and discount rate beta portfolios, in periods of high disagreement. For cash flow beta portfolios, the positive or flat slope has been replaced by a downward trend.

However, it is reassuring to observe that some of the key elements are still present in this setting. Albeit in a less pronounced way, there is still a clear difference in the risk-return relationship between low and high disagreement periods. To some extent, the two-piece curve observed in high disagreement for cash flow betas is still present. The underlying logic appears consistently across these modifications, which leads us to believe that the results we obtain do not depend on certain specific time intervals being – perhaps by chance – assigned to low or high disagreement periods. [13]

2.4 Concluding Remarks

In this chapter we have considered the relationship between stocks and their sensitivity to common market factors. Firstly, we used a vector autoregression approach to separate market news into two components: news related to cash flows and news related to discount rates, and thus move from working from the traditional β measure of sensitivity to systematic risk to two distinct measures, β_{CF} and β_{DR}. Additionally, we bring light to the impact that market disagreement has on this analysis.

In accordance with most of the existing literature, we do not observe what theory has led us to expect, i.e. a relatively linear curve that displays a constant positive slope with respect to β. What sets our results apart from the existing literature is that we are able to investigate separately the impact of disagreement on cash flow and discount rate betas.

We show that, when looking at discount rate betas[14], the relationship is actu-

[13] The authors have performed variations around these robustness checks and found these results consistent with what has been reported.

[14] Which are referred as the "Good Betas" in the famous dichotomy proposed by Campbell and Vuolteenaho (2004).

Figure 2.12: Returns, betas, and detrended disagreement – winsorizing and 2-year MA
Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months for months in the bottom quartile of aggregate disagreement (blue circles) and months in the top quartile of aggregate disagreement (red circles). Aggregate disagreement is the monthly β-weighted average of stock-level disagreement measures as the standard deviation of analyst forecasts for EPS, which has been first winsorized at the 0.1% level, and then detrended by the 2-year moving average.

ally negative. In market states in which there is a higher level of disagreement among market participants, stocks with a high discount rate beta have lower returns than stocks with lower discount rate betas. In low disagreement states, we observe a two-piece curve, with an increasing part until a certain level of discount rate beta, after which we observe a decreasing slope.

This indicates that cash flow betas do seem to carry a higher risk premium, which confirms the results obtained in the ICAPM derivation of Campbell and Vuolteenaho (2004). However, this is only the case in months of low disagreement. In months of high disagreement, the risk-reward relationship breaks down, associating lower returns to riskier stocks. These results have proven robust to modifications in the definition of the time series of disagreement.

It also indicates that disagreement seems to contain a market-wide component which exerts an influence on the valuation of financial assets, consistent with the hypothesis of Miller (1977) in which the price signal carried by certain investors is not transmitted to the market if the dispersion of beliefs is sufficiently large, and limits to arbitrage bind their short sale behavior.

Our main contribution resides in establishing the following: (1) To properly assess the influence of disagreement, it is important to consider an aggregate, market-wide measure. Our results show that while it is true that stock-level measures play an important role, disagreement matters also decisively at the market-level. (2) When considering the impact of disagreement on returns, it matters to be able to differentiate between cash flow and discount rate betas, with the latter performing a much more dramatic role than the former in situations of high disagreement.

Chapter 3

It Takes Two to Tango

Disagreement and Sentiment enlighten the Risk and Return relationship

3.1 Introduction

The relationship between the risk of a financial asset and its expected return is at the heart of asset pricing. The Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) provides a model to depict this relationship, using market beta as a risk measure, and expecting a positive link between risk and return.

In practice, however, high-risk assets often deliver lower expected returns than low-risk assets, a fact that has led to an investigation nearly as old as the CAPM itself. Black (1972) is among the first to address it. More recently, Baker et al. (2011) have shown that the performance of stocks is actually declining with market beta. What are the factors that might explain this puzzle?

The idea of incorporating the impact of human behaviour biases in the analysis of financial markets can be traced back at least to Keynes (1936). The manner through which behavioral aspects influence stock markets have often been apprehended through the concepts of limits to arbitrage. Miller (1977) postulates that short-selling constraints among investors can lead to situations of overpricing. Shleifer and Vishny (1997) show that arbitrage can still be risky even when ignoring possible shorting costs. Barber and Odean (2008) add to the analysis by establishing that individual investors are reluctant to hold short positions. All these factors provide a framework which show how behavioral biases can have long-lasting and measurable repercussions on the aggregate market outcomes.

While the existence of behavioral biases is a firmly grounded finding in investor behavior, and the manner trough which they influence the market is increasingly identified, still recently, Hirshleifer (2015) still maintained that:

> There is a need for more theory and testing of the effects of feelings on financial decisions and aggregate outcomes. Especially, the time has come to move beyond behavioral finance to social finance, which studies the structure of social interactions, how financial ideas spread and evolve, and how social processes affect financial outcomes.

One of the most promising and widely discussed prisms through which researchers can study the impact of behavioral biases on markets is the the concept of investor sentiment. It has been shown to drive stock returns in the short run in studies such as Simon and Wiggins (2001), Brown and Cliff (2004), while longer-term effects have been the focus in papers such as Chung et al. (2012). Stambaugh et al. (2012) investigate the role of investor sentiment in a large set of anomalies in cross-sectional returns ; and Yu and Yuan (2011) consider how the mean-variance relationship is impacted by the fluctuations of market sentiment.

In the previous chapter, we showed how taking into account the impact of disagreement among market participants enabled to gain key insights into the risk-return relationship. One might wonder, did our results really capture an effect of market disagreement, or did we end up analyzing investor sentiment, and confusing one with the other?

While disagreement has been the subject of previous studies, it has generated much less interest in the academic literature than the concept of investor sentiment. Sometimes the former is considered as merely a different manifestation of the latter[1], a fact that justifies even more a careful investigation in the relative importance of both concepts.

Accordingly, in this chapter, we will try to disentangle the impact of disagreement and sentiment on the risk-return relationship of stocks. To do so, we will once again leverage the decomposition of returns approach pioneered by Campbell and Shiller (1988a,b), later implemented in Campbell and Vuolteenaho (2004) to consider more closely the exposure to cash flow news and discount rate news, which they termed the "bad beta" and "good beta" of a stock, given their relative price of risk. Other more recent examples of research using the decomposition framework include Botshekan et al. (2012), or Garrett and Priestley (2012).

To our knowledge, our work is the first to consider the joint impact of separate measures of disagreement and sentiment on the association between returns and risk of stocks, captured through separate cash flow and discount rate betas. Several studies, however, have focused on some of those elements separately. Stambaugh et al. (2012), who investigate the role of investor sentiment in

[1] See for instance the presentation in Shefrin (2008).

a set of anomalies in the cross section of stock returns, find that each anomaly is stronger in months following high levels of sentiment. Studies that consider the influence of disagreement, but focus on stock-level estimations, include Diether et al. (2002), who find that stocks with high levels of dispersion of earnings forecasts tend to earn lower returns, or Chen et al. (2002), who come to a similar conclusion using breadth of ownership as their proxy for stock-level disagreement. More recently, Hong and Sraer (2016), with the help of an aggregate, market-wide, measure of disagreement, show that it influences the risk-return relationship by leading, in situations of higher disagreement, to overpriced high-beta stocks. Botshekan et al. (2012) examine cash flow and discount rate betas in up and down markets, but their design, while similar to some degree in the general approach, differs by the actual implementation. In their design, they split their cash flow betas and discount rate betas to establish two separate estimates, conditional on up- or down-market movements in the previous period.

Our paper is structured as follows. In Section 3.2, we describe our data collecting process, detail the empirical procedures we used, and relate them to existing works. In Section 3.3, we will provide an exploration of our results, and put them in perspective with previous literature. Section 3.4 concludes.

3.2 Methodology

3.2.1 Sample Construction

The main source for the data used in this paper is S&P Capital IQ. We start from a sample of 27,719 publicly listed US companies. We remove those for which Capital IQ ends up returning an error, and obtain 27,253 companies. We remove the companies for whom there never was more than 4 analysts, which amounts to 20,612 companies, and obtain a new total of 6,641 companies. We remove those for which, if there was analyst coverage, it was by fewer than four on average, a criteria which is met for 1,910 companies in our sample. Our new total is 4,731 companies. 2,538 of them do not have the US dollar as both their listing currency, and the currency used for their estimates reporting.

From the remaining 2,193 companies, following Jegadeesh and Titman (2001), we do not include in our sample stocks for which the valuation is below USD 5, in order to ensure that our results are not overly driven by small and illiquid stocks, or by the bid-ask bounce. Several identifiers return error codes for all or part of their data when queried in the database, and are thus also removed. Our final sample is composed of 2,085 companies.

3.2.2 Decomposition of Returns

The Return-Decomposition Framework

We refer the reader to Section 2.2.2 for the description of the methodology used in the decomposition of returns.

3.2.3 Time Series for Sentiment and Disagreement

Our market-wide estimate for investor sentiment is the one proposed by Baker and Wurgler (2006). Their sentiment index is formed by taking the first principal component of six measures of investor sentiment, which are the closed-end fund discount, the number and the first-day returns of IPOs, NYSE turnover, the equity share in total new issues, and the dividend premium. The principal component analysis allows them to filter idiosyncratic signal from the individual components to obtain a common component, which is the index we use.

We use the same time series for disagreement as the one in the previous chapter. In a first stage we measure stock-level disagreement as the dispersion in analysts' forecasts of the EPS at the end of current fiscal year. To come up with an aggregate measure of market disagreement, we use a weighting scheme in the same vein as Yu (2011) and Hong and Sraer (2016). Each month, we use past weekly returns (with a minimum of 30 weeks and a maximum of 80 weeks) to regress the stock's return on the contemporaneous market return. We then sort stocks in 20 beta portfolios based on these pre-ranking betas. We compute the monthly equal-weighted returns on these portfolios. We then compute post-ranking betas by regressing each portfolio returns on the market returns. These post-ranking betas are computed using the entire sample period, following Fama and French (1992).

We then weight each month stock-level dispersion of forecasts by these post-ranking betas.

Figure 3.1 show the market-wide time series for disagreement and sentiment that we are gonna use in our analysis.

3.2.4 Estimation of returns by portfolio

At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. We compute equal-

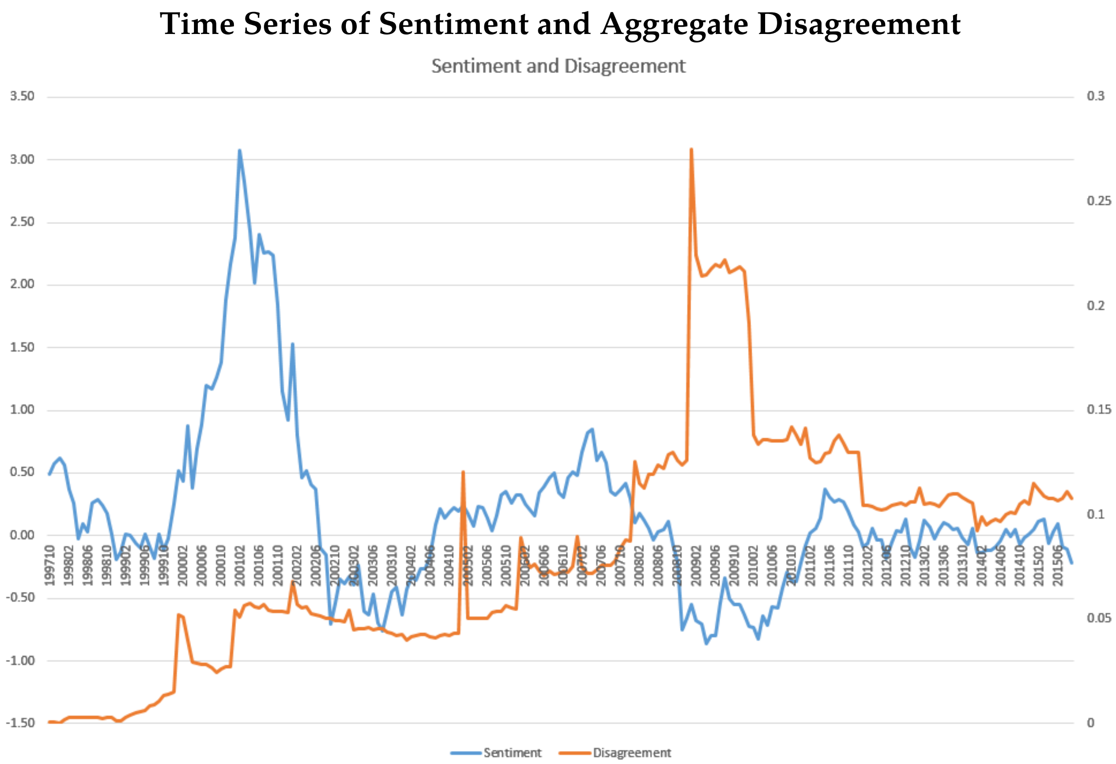

Figure 3.1: Time Series of Sentiment and Aggregate Disagreement
Sample period: 12/1996 to 12/2015. Sample: Stocks in the Capital IQ database, excluding stocks with price < \$5. *Disagreement:*Each month, we calculate for each stock the standard deviation of analyst forecasts for the EPS, our measure of stock-level disagreement. We use portfolio post-ranking betas to weight each individual stock's dispersion of forecasts to obtain a monthly, aggregate disagreement measure. *Sentiment:* We use the sentiment time series proposed by Baker and Wurgler (2006).

weighted excess returns (over the risk-free rate) for each of our 40 portfolios over a period of 1, 3, 6, and 12 months.

3.3 Results

Our main results are represented in Figure 3.2 [2]. In this Figure, we make the distinction between forward excess returns from month in four different combinations of disagreement and sentiment market states. Each of these combinations are represented by a separate curve.

Several elements can be discerned from visual inspection. First of all, in all configurations, our four curves are distinguishable from one another. Neither sentiment nor disagreement appears to drive results at the expense of the other factor, to the extent that, for instance, forward excess returns in low disagreement months show a different dynamic depending on whether these low disagreement months happen to experience low or high levels of market sentiment.

More precisely, we observe that the security market line is flat for months in the low sentiment, high disagreement configuration, displays a positive slope in months of low disagreement and low sentiment, and a negative slope in months of high sentiment, but markedly more so when disagreement is also high.

Finding a negative slope for the security market line in periods of high sentiment agrees with Antoniou et al. (2016), who find in their study (which considers sentiment only) that the security market line appears in accordance with the capital asset pricing model in pessimistic periods, but is downward sloping during optimistic periods. They posit that this is due to optimism attracting traders in riskier investment opportunities, in the form of high beta stocks, driving prices high and returns low, whereas such traders are less active in pessimistic periods. Our results are consistent with their findings, but also show that this is decisively more so in periods in which disagreement is also high. In the case of cash flow betas, this is less pronounced for lower beta stocks, while the slope is more pronounced for all values of betas in the case of discount rate betas. Rationales for negative associations between risk and return when considering the influence of sentiment are also presented in the reference work of Shefrin (2008).

These results are also consistent with Yu (2011), who find that the relationship between risk and return, while positive when the Baker-Wurgler index is low, is

[2] In this and other figures which contain four separate series, while we felt it was worthwhile, for comparison purposes, to include them in the same graph, doing so impeded slightly on the readability of the figures. To help with series identification, we made the choice to add smoothing splines. These should not be interpreted as carrying information with regards to levels of statistical significance.

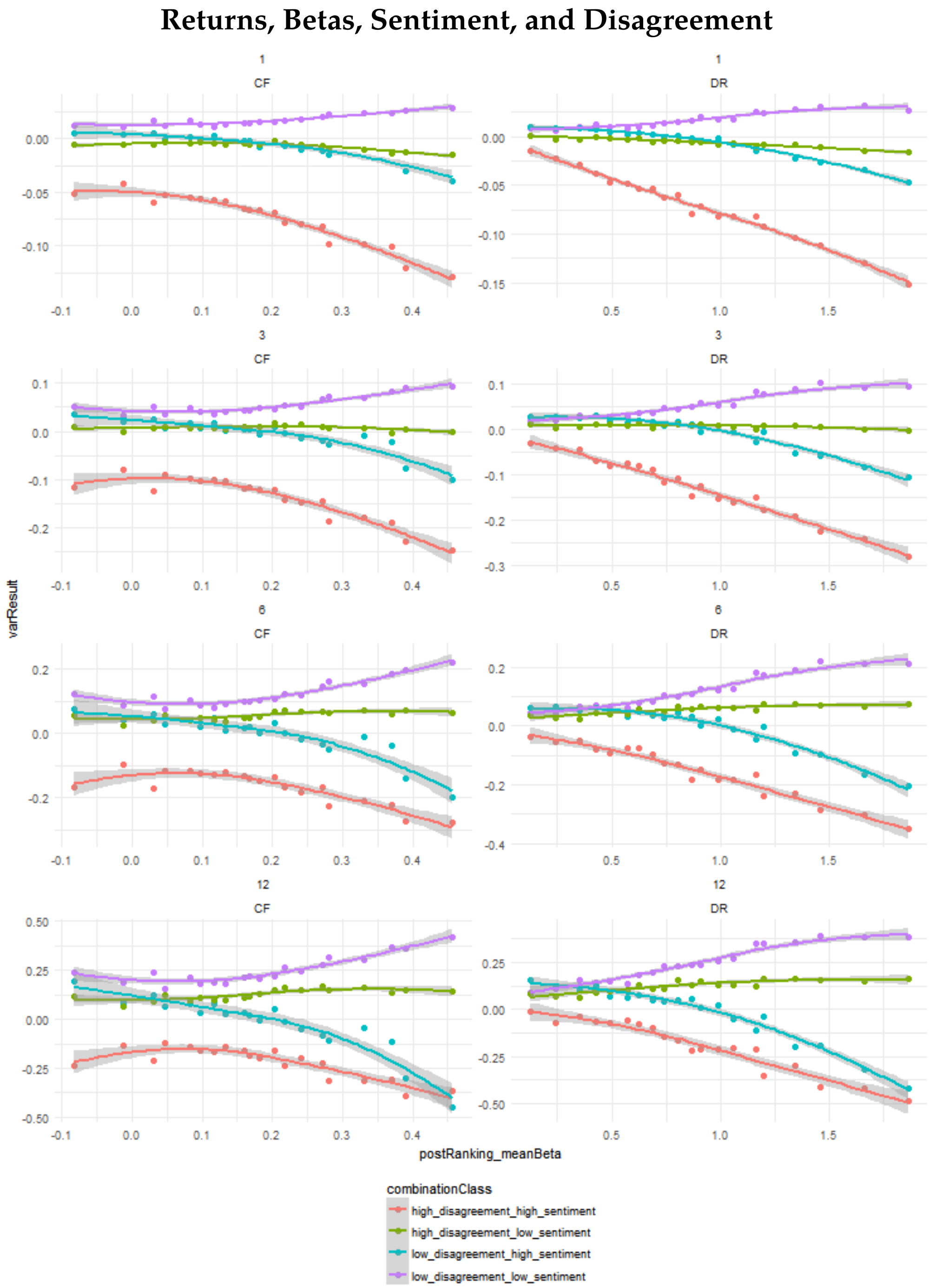

Figure 3.2: Returns, Betas, Sentiment, and Disagreement

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Cash Flow and Discount Rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios for both Cash Flow betas and Discount Rate betas. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months for months in the bottom and top quartiles of aggregate disagreement and sentiment. *Disagreement:* Each month, we calculate for each stock the standard deviation of analyst forecasts for the EPS, our measure of stock-level disagreement. We use portfolio post-ranking betas to weight each individual stock's dispersion of forecasts to obtain a monthly, aggregate disagreement measure. *Sentiment:* We use the sentiment time series proposed by Baker and Wurgler (2006). *Note:* Curves and shaded areas are smoothing splines provided to aid with series identification and pattern recognition, and should not be interpreted as carrying information with regards to level of statistical significance.

weakened when it is high. This also agrees with Barone-Adesi et al. (2013), who find that the risk-return relationship can be negative due to excessive optimism[3].

While our results confirm previous empirical findings with regards to sentiment, they also bring to light that incorporating disagreement in the analysis also proves decisive. Hong and Sraer (2016) find that high beta stocks display a "kick" in their security market line in periods of high disagreement, due to the fact that in such a situation, some investors facing short-selling limitations, such as mutual funds, are not able to carry their price signal to the market, leading overly optimistic investors to overprice higher beta stocks, and driving their returns down. We can see that such an effect can be seen in our results, with the purple curve corresponding returns obtained during low disagreement, low investment months, experiencing a downgrade in high beta returns, both for cash flow and discount rate betas, in higher disagreement months, which correspond to the green curve. This effect is less visible for high sentiment months, in which there is still a decisive difference according to the level of disagreement, but more at a level basis, especially for middle values of cash flow and discount rate betas.

When considering differences between cash flow and discount rate betas, the main contrast appear in periods of high sentiment. For cash flow betas, in months of high disagreement and high sentiment, the security market line appears flat for low to medium values of betas, while the slope is negative for all values of discount rate betas. We also observe that the concavity for low disagreement, high sentiment months appears higher for cash flow betas. We propose a robustness check, that replicated Figure 3.2 for portfolios based on standard betas (and not with cash flow and discount rate betas) in the following subsection.

Another investigation in the respective influence of disagreement and sentiment on returns is presented in Tables 3.1 to 3.3. In these, we present another way to assess the information presented in Figure 3.2, for respectively standard betas portfolios, cash flow betas portfolios, and discount rate beta portfolios. In each of these, Panel A examines, within market states characterized by similar level of aggregate disagreement, the impact of sentiment variations. Panel B does the same for the opposite contrast, that is to say, we observe the relative impact of disagreement variations within months in the same quartile of sentiment levels. The row "Difference" is calculated by taking the squared difference of the two previous rows, and the mean of these differences is mentioned in the line separating each sub-panel.

What we observe in Table 3.2, for cash flow betas portfolios, is that the mean

[3] and also, in their design, to overconfidence, a feature which we are not able to investigate at this stage

Table 3.1: Sentiment split vs. Disagreement split, Standard Beta Portfolios

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation standard betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The table shows differences in excess returns across two-way splits of the sample, one in the time series of aggregate market disagreement, and the other in the time series of market sentiment. In Panel A, for each standard portfolio, we hold constant the level of market disagreement in each sub-panel, and compare average excess returns in periods of high and low sentiment. In Panel B, the two sub-panels correspond to periods characterized by low and high sentiment, in which we compare the average excess returns in low and high aggregate disagreement states. The line "Difference" corresponds to the squared difference in excess returns.

Standard Portfolio	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
PANEL A : WITHIN MARKET DISAGREEMENT STATES, THE IMPACT OF SENTIMENT VARIATIONS																				
Low Disagreement – Mean Difference : 0.0119																				
Low Sentiment	0.0893	0.0654	0.0475	0.0389	0.0303	0.0308	0.0246	0.0310	0.0214	0.0085	0.0059	0.0139	0.0078	0.0160	0.0148	0.0245	0.0454	0.0531	0.0581	0.1983
High Sentiment	0.3233	0.1171	0.0905	0.0719	0.0681	0.0815	0.0847	0.1031	0.0982	0.0927	0.1013	0.0951	0.0924	0.0934	0.0816	0.0772	0.0664	0.0627	-0.0515	-0.1240
Difference	0.0548	0.0027	0.0018	0.0011	0.0014	0.0026	0.0036	0.0052	0.0059	0.0071	0.0091	0.0066	0.0072	0.0060	0.0045	0.0028	0.0004	0.0001	0.0120	0.1039
High Disagreement – Mean Difference : 0.0262																				
Low Sentiment	-0.0546	-0.0084	0.0021	-0.0005	0.0034	0.0090	0.0035	-0.0016	0.0029	0.0040	0.0109	0.0116	0.0184	0.0247	0.0165	0.0252	0.0333	0.0483	0.0362	0.1792
High Sentiment	0.0767	0.0008	0.0038	0.0006	-0.0193	-0.0054	-0.0023	-0.0012	-0.0227	-0.0218	-0.0063	-0.0309	-0.0202	-0.0361	-0.0565	-0.0560	-0.0607	-0.0890	-0.1356	-0.4751
Difference	0.0172	0.0001	0.0000	0.0000	0.0005	0.0002	0.0000	0.0000	0.0007	0.0007	0.0003	0.0018	0.0015	0.0037	0.0053	0.0066	0.0088	0.0189	0.0295	0.4281
PANEL B : WITHIN MARKET SENTIMENT STATES, THE IMPACT OF DISAGREEMENT VARIATIONS																				
Low Sentiment – Mean Difference : 0.0017																				
Low Disagreement	0.0893	0.0654	0.0475	0.0389	0.0303	0.0308	0.0246	0.0310	0.0214	0.0085	0.0059	0.0139	0.0078	0.0160	0.0148	0.0245	0.0454	0.0531	0.0581	0.1983
High Disagreement	-0.0546	-0.0084	0.0021	-0.0005	0.0034	0.0090	0.0035	-0.0016	0.0029	0.0040	0.0109	0.0116	0.0184	0.0247	0.0165	0.0252	0.0333	0.0483	0.0362	0.1792
Difference	0.0207	0.0054	0.0021	0.0016	0.0007	0.0005	0.0004	0.0011	0.0003	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000	0.0000	0.0001	0.0000	0.0005	0.0004
High Sentiment – Mean Difference : 0.0206																				
Low Disagreement	0.3233	0.1171	0.0905	0.0719	0.0681	0.0815	0.0847	0.1031	0.0982	0.0927	0.1013	0.0951	0.0924	0.0934	0.0816	0.0772	0.0664	0.0627	-0.0515	-0.1240
High Disagreement	0.0767	0.0008	0.0038	0.0006	-0.0193	-0.0054	-0.0023	-0.0012	-0.0227	-0.0218	-0.0063	-0.0309	-0.0202	-0.0361	-0.0565	-0.0560	-0.0607	-0.0890	-0.1356	-0.4751
Difference	0.0608	0.0135	0.0075	0.0051	0.0076	0.0076	0.0076	0.0109	0.0146	0.0131	0.0116	0.0159	0.0127	0.0168	0.0191	0.0177	0.0162	0.0230	0.0071	0.1233

Table 3.2: Stock-Level Dispersion of Forecasts vs. Aggregate Market Disagreement, CF Portfolios

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation cash flow and discount rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The table shows differences in excess returns across two-way splits of the sample, one in the time series of aggregate market disagreement, and the other in the time series of market sentiment. In Panel A, for each standard portfolio, we hold constant the level of market disagreement in each sub-panel, and compare average excess returns in periods of high and low sentiment. In Panel B, the two sub-panels correspond to periods characterized by low and high sentiment, in which we compare the average excess returns in low and high aggregate disagreement states. The line "Difference" corresponds to the squared difference in excess returns.

CF Portfolio	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
PANEL A : WITHIN MARKET DISAGREEMENT STATES, THE IMPACT OF SENTIMENT VARIATIONS																				
Low Disagreement – Mean Difference : 0.0287																				
Low Sentiment	0.1254	0.0987	0.1353	0.0847	0.1231	0.1007	0.1007	0.0894	0.1134	0.1100	0.1030	0.1137	0.1204	0.1186	0.1477	0.1739	0.1547	0.1877	0.1903	0.2181
High Sentiment	0.0686	0.0266	0.0408	0.0332	0.0220	0.0203	0.0377	0.0246	0.0092	0.0207	0.0013	0.0257	-0.0073	-0.0125	-0.0320	-0.0549	-0.0066	-0.0333	-0.1459	-0.2144
Difference	0.0032	0.0052	0.0089	0.0027	0.0102	0.0065	0.0040	0.0042	0.0109	0.0080	0.0103	0.0077	0.0163	0.0172	0.0323	0.0523	0.0260	0.0488	0.1130	0.1871
High Disagreement – Mean Difference : 0.0535																				
Low Sentiment	0.0655	0.0131	0.0439	0.0576	0.0426	0.0562	0.0403	0.0407	0.0504	0.0500	0.0584	0.0700	0.0711	0.0642	0.0659	0.0631	0.0679	0.0556	0.0672	0.0673
High Sentiment	-0.1623	-0.0810	-0.1759	-0.1163	-0.1329	-0.1232	-0.1280	-0.1196	-0.1279	-0.1537	-0.1391	-0.1600	-0.1545	-0.1868	-0.1710	-0.2229	-0.2060	-0.2367	-0.2780	-0.2736
Difference	0.0519	0.0089	0.0483	0.0302	0.0308	0.0322	0.0283	0.0257	0.0318	0.0415	0.0390	0.0529	0.0509	0.0630	0.0561	0.0818	0.0750	0.0854	0.1192	0.1162
PANEL B : WITHIN MARKET SENTIMENT STATES, THE IMPACT OF DISAGREEMENT VARIATIONS																				
Low Sentiment – Mean Difference : 0.0067																				
Low Disagreement	0.1254	0.0987	0.1353	0.0847	0.1231	0.1007	0.1007	0.0894	0.1134	0.1100	0.1030	0.1137	0.1204	0.1186	0.1477	0.1739	0.1547	0.1877	0.1903	0.2181
High Disagreement	0.0655	0.0131	0.0439	0.0576	0.0426	0.0562	0.0403	0.0407	0.0504	0.0500	0.0584	0.0700	0.0711	0.0642	0.0659	0.0631	0.0679	0.0556	0.0672	0.0673
Difference	0.0036	0.0073	0.0084	0.0007	0.0065	0.0020	0.0036	0.0024	0.0040	0.0036	0.0020	0.0019	0.0024	0.0030	0.0067	0.0123	0.0075	0.0175	0.0152	0.0227
High Sentiment – Mean Difference : 0.0266																				
Low Disagreement	0.0686	0.0266	0.0408	0.0332	0.0220	0.0203	0.0377	0.0246	0.0092	0.0207	0.0013	0.0257	-0.0073	-0.0125	-0.0320	-0.0549	-0.0066	-0.0333	-0.1459	-0.2144
High Disagreement	-0.1623	-0.0810	-0.1759	-0.1163	-0.1329	-0.1232	-0.1280	-0.1196	-0.1279	-0.1537	-0.1391	-0.1600	-0.1545	-0.1868	-0.1710	-0.2229	-0.2060	-0.2367	-0.2780	-0.2736
Difference	0.0533	0.0116	0.0470	0.0224	0.0240	0.0206	0.0275	0.0208	0.0188	0.0304	0.0197	0.0345	0.0217	0.0304	0.0193	0.0282	0.0398	0.0414	0.0175	0.0035

Table 3.3: Stock-Level Dispersion of Forecasts vs. Aggregate Market Disagreement, DR Portfolios

Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < \$5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation cash flow and discount rate betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The table shows differences in excess returns across two-way splits of the sample, one in the time series of aggregate market disagreement, and the other in the time series of market sentiment. In Panel A, for each standard portfolio, we hold constant the level of market disagreement in each sub-panel, and compare average excess returns in periods of high and low sentiment. In Panel B, the two sub-panels correspond to periods characterized by low and high sentiment, in which we compare the average excess returns in low and high aggregate disagreement states. The line "Difference" corresponds to the squared difference in excess returns.

DR Portfolio	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
PANEL A : WITHIN MARKET DISAGREEMENT STATES, THE IMPACT OF SENTIMENT VARIATIONS																				
Low Disagreement – Mean Difference : 0.0325																				
Low Sentiment	0.0511	0.0435	0.0782	0.0824	0.0692	0.0713	0.0933	0.0912	0.1098	0.0976	0.1048	0.1212	0.1203	0.1213	0.1830	0.1701	0.1949	0.2334	0.1987	0.2200
High Sentiment	0.0951	0.0688	0.0688	0.0622	0.0370	0.0356	0.0523	0.0402	0.0251	0.0367	0.0352	0.0095	0.0296	-0.0141	-0.0463	0.0010	-0.0781	-0.1099	-0.1673	-0.2018
Difference	0.0019	0.0006	0.0001	0.0004	0.0010	0.0013	0.0017	0.0026	0.0072	0.0037	0.0048	0.0125	0.0082	0.0183	0.0526	0.0286	0.0745	0.1179	0.1340	0.1779
High Disagreement – Mean Difference : 0.0554																				
Low Sentiment	0.0406	0.0263	0.0310	0.0465	0.0411	0.0447	0.0530	0.0371	0.0499	0.0677	0.0558	0.0681	0.0593	0.0555	0.0511	0.0844	0.0777	0.0708	0.0718	0.0759
High Sentiment	-0.1441	-0.0516	-0.0598	-0.0822	-0.0957	-0.0827	-0.0859	-0.1041	-0.1217	-0.1273	-0.1819	-0.1469	-0.1931	-0.1888	-0.1668	-0.2360	-0.2337	-0.2812	-0.2898	-0.3396
Difference	0.0341	0.0061	0.0082	0.0166	0.0187	0.0162	0.0193	0.0199	0.0294	0.0380	0.0565	0.0462	0.0637	0.0597	0.0475	0.1027	0.0970	0.1239	0.1308	0.1726
PANEL B : WITHIN MARKET SENTIMENT STATES, THE IMPACT OF DISAGREEMENT VARIATIONS																				
Low Sentiment – Mean Difference : 0.0065																				
Low Disagreement	0.0511	0.0435	0.0782	0.0824	0.0692	0.0713	0.0933	0.0912	0.1098	0.0976	0.1048	0.1212	0.1203	0.1213	0.1830	0.1701	0.1949	0.2334	0.1987	0.2200
High Disagreement	0.0406	0.0263	0.0310	0.0465	0.0411	0.0447	0.0530	0.0371	0.0499	0.0677	0.0558	0.0681	0.0593	0.0555	0.0511	0.0844	0.0777	0.0708	0.0718	0.0759
Difference	0.0001	0.0003	0.0022	0.0013	0.0008	0.0007	0.0016	0.0029	0.0036	0.0009	0.0024	0.0028	0.0037	0.0043	0.0174	0.0073	0.0137	0.0264	0.0161	0.0208
High Sentiment – Mean Difference : 0.027																				
Low Disagreement	0.0951	0.0688	0.0688	0.0622	0.0370	0.0356	0.0523	0.0402	0.0251	0.0367	0.0352	0.0095	0.0296	-0.0141	-0.0463	0.0010	-0.0781	-0.1099	-0.1673	-0.2018
High Disagreement	-0.1441	-0.0516	-0.0598	-0.0822	-0.0957	-0.0827	-0.0859	-0.1041	-0.1217	-0.1273	-0.1819	-0.1469	-0.1931	-0.1888	-0.1668	-0.2360	-0.2337	-0.2812	-0.2898	-0.3396
Difference	0.0572	0.0145	0.0165	0.0209	0.0176	0.0140	0.0191	0.0208	0.0216	0.0269	0.0471	0.0245	0.0496	0.0305	0.0145	0.0562	0.0242	0.0293	0.0150	0.0190

differences appear more pronounced for variations in sentiment than for variations in disagreement. Indeed, the mean squared differences are higher, on average, in Panel A, which aims to capture the impact of *sentiment* variations, with values of 0.0287 and 0.0535, than in Panel B, which aims to capture the impact of *disagreement* variations, with values of 0.0067 and 0.0266. However, we see that the contrast between low and high sentiment is higher when we considering high disagreement periods where the mean difference of 0.0535 is twice as high as the one observed in low disagreement periods of 0.0287. When examining the impact of disagreement, we see that it also displays the highest contrast in periods of high sentiment with a mean squared difference of 0.0266 compared to 0.0067, an observation which is coherent with what had appeared in Figure 3.2.

The situation is extremely similar in the Table 3.3, which depicts the situation for discount rate betas, with the numbers for mean squared differences equal to those obtained for cash flow betas portfolios. Again, what appears is that variations in sentiment drive higher differences in returns than variations in disagreement, but this effect is larger in periods of high disagreement (0.0554 vs 0.0325). The mean squared differences for variations in disagreement are themselves higher in high sentiment periods (0.027 vs 0.0065).

Contrasts are much less marked in Table 3.1, but of similar nature, and similar patterns emerge.

3.3.1 Analysis of Risk Premia

In Table 3.4, we report the estimated prices of risk from the cross-sectional regression of the form

$$R_i - R_f = \lambda_0 + \lambda_{CF}\widehat{\beta}_{CF} + \lambda_{DR}\widehat{\beta}_{DR} + \epsilon_i \tag{3.1}$$

for different market states, and with i being each of our 40 portfolios sorted according to discount rate and cash flow betas. We should point out that there is no intuitive link that should be made between these results and Figure 3.2, because in the latter case, forward excess returns are plotted with respect to the single dimension of cash flow and discount rate betas, while in this case, for each of our 40 test assets, we consider both their equal-weighted mean cash flow and discount rate beta.

What we can gather from Table 3.4, first of all, is that our risk premia are not significative when considering the whole sample, and the estimation brings a somewhat low adjusted R-squared. When considering the four different market states, however, contrasts appear. Risk premia are significant in all case for

Table 3.4: Cross-sectional Prices of Risk, Different Market States

Estimated prices of risk from the cross-sectional regression of the form

$$R_i - R_f = \lambda_0 + \lambda_{CF}\widehat{\beta}_{CF} + \lambda_{DR}\widehat{\beta}_{DR} + \epsilon_i$$

with i being one of our 40 cash flow or discount rate beta-sorted portfolios. Figures in round parentheses are heteroscedasticity-consistent $t-$statistics while figures in square parentheses are partial R^2 coefficients. The partial R^2 is the squared partial correlation coefficient, where the partial correlation coefficient measures the correlation between an explanatory variable and the dependent variable given the other explanatory variables. ***, ** and * denote significance at the 1, 5, and 10% levels respectively.

PANEL A : WHOLE SAMPLE		
λ_{CF}	λ_{DR}	$\overline{R^2}$
-0.0072	0.0003	0.1545
(-1.1167)	(0.2681)	
[0.046]	[0.0015]	
PANEL B : DISAGREEMENT / SENTIMENT SPLIT		
PANEL B-1 : Low Disagreement – Low Sentiment		
λ_{CF}	λ_{DR}	$\overline{R^2}$
-0.0286	0.0315***	0.8846
(-1.3645)	(5.8955)	
[0.1019]	[0.6544]	
PANEL B-2 : Low Disagreement – High Sentiment		
λ_{CF}	λ_{DR}	$\overline{R^2}$
0.0803**	-0.0914***	0.9333
(2.271)	(-9.8335)	
[0.1599]	[0.7721]	
PANEL B-3 : High Disagreement – Low Sentiment		
λ_{CF}	λ_{DR}	$\overline{R^2}$
-0.0203**	0.0072***	0.2166
(-2.3535)	(3.2775)	
[0.1385]	[0.2195]	
PANEL B-4 : High Disagreement – High Sentiment		
λ_{CF}	λ_{DR}	$\overline{R^2}$
0.0673	-0.1483***	0.9705
(1.4557)	(-12.1679)	
[0.0853]	[0.8614]	

discount rate betas, and found to be negative in states of high sentiment, and positive in states of low sentiment. This result appears to be in concordance with results mentioned before, among those Antoniou et al. (2016). The results are much less conclusive with respect to premia associated with cash flow betas, which are found to be significant in mixed states of low and high disagreement or sentiment.

A feature of note is that the estimation brings higher values for adjuted R-squared in the case of high sentiment and high disagreement, in accordance with evidence we gathered from Figure 3.2.

3.3.2 Robustness check – Decomposition of Returns

In Figure 3.3, we replicate the analysis of Figure 3.2, but this time we do not base our forward excess returns on portfolios based on cash flow and discount rate betas, but rather on standard, CAPM betas.

We see that the same patterns that we observed before can be found back for this analysis, although the contrast is much less clear, and results appear overly driven by returns obtained on the highest beta-portfolios. In figures which are not included in the present document, but which are available on request, we see that when plotting the same curve and ignoring the highest one or two standard beta portfolios, we are not able to observe the dynamics we obtained when decomposing standard betas in cash flow and discount rate betas.

3.3.3 Robustness Check – No disagreement split

Finally, as a last robustness check, we replicate the graphs we obtained in Figure 3.2, but this time we only distinguish between forward excess returns in month belonging to the lowest and highest quartiles of the sentiment distribution. We obtain results consistent with Antoniou et al. (2016) among others, who find that the security market line is negative in periods of high sentiment. For time horizons of 3 months and higher, the security market line appears to display a positive slope in low sentiment months, and a decisively negative slope in months of high sentiment. This also agrees with Barone-Adesi et al. (2013).

We also see, however, that ignoring the influence of disagreement at this analysis prevents us from observing some key elements that we had examined in Figure 3.2, in which we saw that a positive slope in the security market line is only observed in months of both low sentiment and low disagreement, and that the returns are much lower, much more quickly, in months of high sentiment and high disagreement.

Returns, Betas, Sentiment, and Disagreement – No decomposition of returns

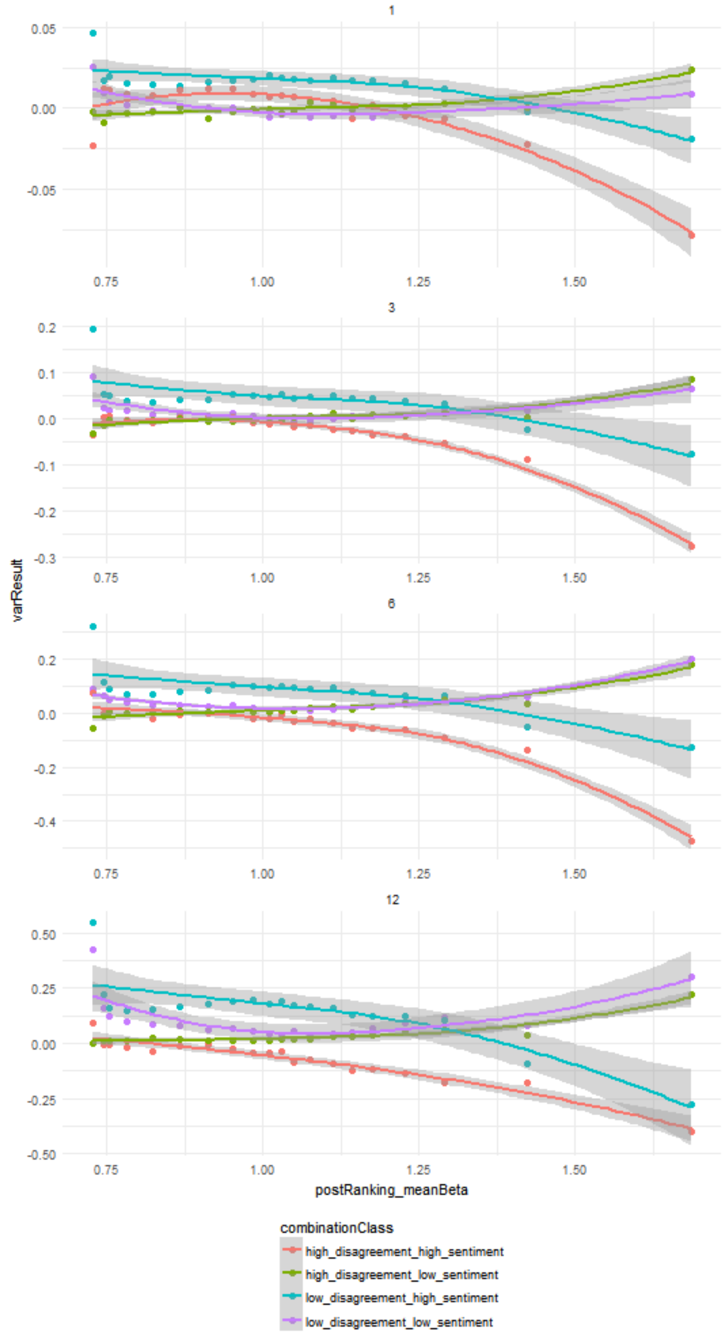

Figure 3.3: Returns, Betas, Sentiment, and Disagreement – No decomposition of returns
Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < \$5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Standard betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months for months in the bottom and top quartiles of aggregate disagreement and sentiment. *Disagreement:* Each month, we calculate for each stock the standard deviation of analyst forecasts for the EPS, our measure of stock-level disagreement. We use portfolio post-ranking betas to weight each individual stock's dispersion of forecasts to obtain a monthly, aggregate disagreement measure. *Sentiment:* We use the sentiment time series proposed by Baker and Wurgler (2006). *Note:* Curves and shaded areas are smoothing splines provided to aid with series identification and pattern recognition, and should not be interpreted as carrying information with regards to level of statistical significance.

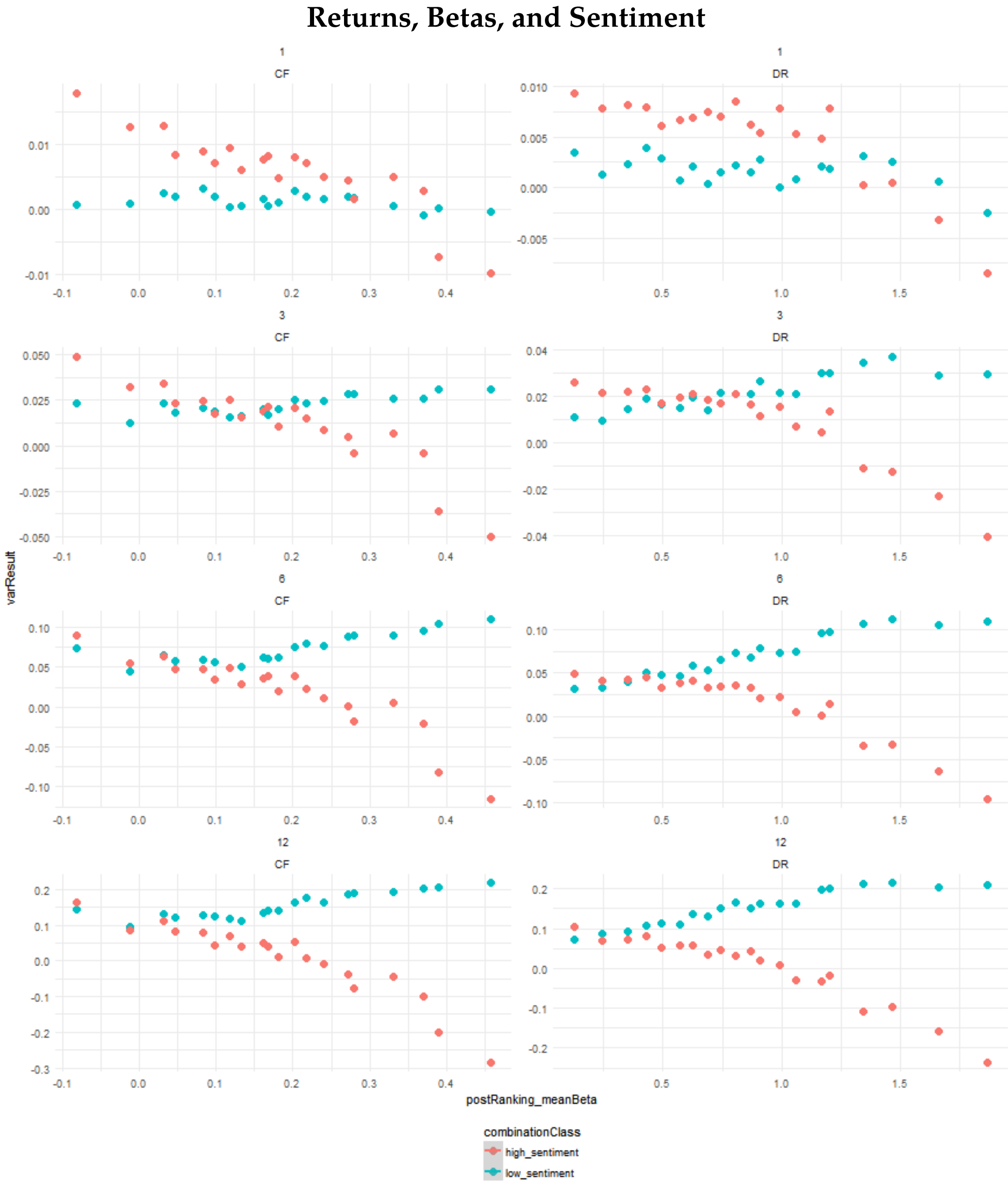

Figure 3.4: Returns, Betas, and Sentiment
Sample period: 1/1990 to 12/2015. Stocks in the Capital IQ database, excluding penny stocks (price < $5). At the beginning of each calendar month, stocks are ranked in ascending order on the basis of the ratio of their estimated beta at the end of the previous month. Preformation Standard betas are estimated over a period not shorter than 30 weeks. The ranked stocks are assigned to 1 of 20 equal-weighted portfolios. The graph plots the average excess returns over a period of 1, 3, 6 and 12 months for months in the bottom and top quartiles of aggregate sentiment. *Sentiment:* We use the sentiment time series proposed by Baker and Wurgler (2006).

3.4 Concluding Remarks

In this chapter, we used the two prisms of investor sentiment and market disagreement to examine the return dynamics of stocks and decomposed betas. Our key findings are the following. (1) When we look at disagreement, as we did in Chapter 2, we are not merely looking at another facet of sentiment. We have shown that while our results are consistent with existing literature when we consider only the impact of sentiment, we are also able to disentangle a separate impact of disagreement in this regard. (2) Our results suggest that there is an interaction between sentiment and disagreement. The effect of disagreement is magnified in periods of high sentiment. A traditional, upward-sloping security market line is only observed in periods of low disagreement and low sentiment, while the inversion of this relationship is the most pronounced, in accordance with extant literature, in periods of not only comparatively high sentiment, but also high disagreement. (3) Being able to consider the separate impact on cash flow and discount rate betas allows us not only to better discern the interactions between disagreement and sentiment, but also brings to light the added importance of discount rate betas in the situations in which things are most dire: when investors agree and seem confident.

The existing literature was justified to emphasize the role of sentiment, but by neglecting its important interplay with disagreement when examining the dynamics of risk and returns, most forgot that, in this matter as in others, it takes two to tango.

Chapter 4

Cracks in the Crystal Ball

Foreign exchange rate exposure when forecasters disagree [1]

4.1 Introduction

Foreign exchange rate volatility and its impact on firms' operations is a matter of crucial interest to managers, investors and public authorities. However, although it is clear from a theoretical perspective that exchange rates affect both firms' future cash flows and their cost of capital, most attempts to empirically assess the impact of currency movements on firm value have met with mixed results (Jorion, 1990; He and Ng, 1998; Griffin and Stulz, 2001). The way firms' exposure should be measured has thus grown over the years to a central debate. While a whole strand of the literature investigates the inclusion of more sophisticated definitions of firm-specific (Bartram et al., 2010; Chang et al., 2013) or market-wide (Chaieb and Mazzotta, 2013) drivers of foreign exchange risk exposure, much progress has been made in the specification of the exchange rate factor used to measure firms' currency exposure, too. One of the first studies in this area by Dominguez and Tesar (2001) demonstrates that since trade-weights do not correspond with individual firms' or industries' trade patterns, the use of trade-weighted exchange rate indices leads to an underestimation of the impact of exchange rate shocks. Alternatively, Amihud (1994) raises very early the concern that documented findings may be biased because previous research designs ignore the fact that empirically observed exchange rate variations may have been partly anticipated. While the new specification of the currency factor by Amihud (1994) only marginally increases the significance of firms' exchange rate expo-

[1] This chapter is based on the working paper of the same name, co-authored with A. Muller, W.F.C. Verschoor, and R.C.J. Zwinkels.

sures, subsequent papers (Gao, 2000; Jongen et al., 2012) have shown that unexpected currency movements have significantly stronger effects on firm value than total exchange rate movements.

From a theoretical perspective, measuring foreign exchange risk exposure as firm values' sensitivity to unexpected currency fluctuations is consistent with Adler and Dumas (1984) seminal definition of foreign exchange rate exposure. Foreign exchange rate exposure should be measured with respect to unexpected currency fluctuations because expected currency fluctuations have already been incorporated in estimations of firms' future cash flows and their cost of capital. When relaxing the random walk hypothesis of exchange rate movements and defining foreign exchange rate movement innovations with respect to currency fluctuations expectations, the question of the most reliable currency forecasts needs to be sorted out. While Gao (2000) refers to fundamental macroeconomic forces, Jongen et al. (2012) use both derivative market information and analysts' forecasts. The latter suggest that unexpected exchange rate movements measured with respect to analysts' forecast have the strongest impact on firm value.

Surprisingly, so far, none of these papers has questioned how differential accuracy levels of exchange rate anticipations used to build the unexpected exchange rate factor may impact the estimation of currency risk exposure. None of these papers makes a distinction between periods where uncertainty on foreign exchange rate markets is so high that market participants' express extremely dispersed opinions about future exchange rate movements and periods where market participants believe to observe precise and coherent opinions about the future path of exchange rates. The commentary calls for more research on how currency forecasts' statistical properties affect the degree to which these forecasts proxy underlying markets' expectations and the degree to which they are (or are not) incorporated in market prices. The relationship between a signal's presumed informational quality and the way the signal is incorporated in financial markets has been extensively discussed. When focusing specifically on exchange rate forecasts, dispersion is shown to be a key ingredient in explaining the variation of the valuation impacts of these forecasts (Chen et al., 2005). Therefore, our paper aims to document, across different levels of exchange rate forecast dispersion, how stock markets are affected either by unexpected exchange rate movements or - as traditionally measured - by total exchange rate movements. Our main goal is to explain when total exchange rate movements may be considered as poorly performing risk factors to measure firms' currency exposure - in other words when the decomposition of these exchange risk factors in expected and unexpected currency movements enable us to build more reliable and economically meaningful measures of the forces that are really influencing multinationals' stock returns. The paper complements thus our understanding of firms' foreign exchange rate exposure estimation by documenting when and how differentially characterized anticipations about future exchange rate movements affect our assessment of firms' currency exposure.

On a large sample of US multinationals that are active in Europe and Japan this paper makes two important contributions: (1) We disaggregate total exchange rate movements in unanticipated and expected exchange rate movements; and investigate in how far unanticipated exchange rate shocks but also revisions in exchange rate forecasts affect the value of US multinationals. According to our empirical findings, this decomposition of the exchange rate factor clearly reveals that investors are very sensitive to exchange rate forecast revisions (Jongen et al., 2012) and in line with previous studies that they also react to new exchange rate movement signals to the extent to which they differ from what had been expected in the past. Our results suggest furthermore that the impact of this disaggregated exchange rate factor is unequivocally stronger than the impact of the most frequently used exchange rate factor previously used in the literature (Jorion, 1990). (2) In a second stage we conjecture that the degree of heterogeneity among exchange rate forecasts (which may be considered as a good proxy for the level of market disagreement) has a direct negative influence on the market response to exchange rate forecasts as well as on the degree to which stock movements are significantly exposed to unanticipated currency shocks. In line with our expectations we observe that in stronger disagreement periods the valuation impact of unexpected exchange rate movements is lower. In contrast, when market participants agree about their forecasts, investors lend more credibility to these forecasts and stock prices are more significantly affected by unexpected shocks than by total exchange rate movements.

A preliminary section of this paper details the motivation of the disaggregation of the exchange rate factor. In the third section, we describe our data sample and the research design. Empirical findings are discussed in section four and we conclude in section five.

4.2 Motivation

In their seminal article, Adler and Dumas (1984) proposed to interpret foreign exchange risk exposure as the sensitivity of the domestic-currency value of any physical or financial asset to unanticipated exchange rate movements. In their work the exposure of an asset was estimated by regressing its domestic-currency market return on the contemporaneous unanticipated exchange rate change. As other variables might covary with exchange rate movements and stock returns, omitting them might lead to an overestimation of the proportion of variance attributable to foreign currency movements.define foreign exchange risk exposure as the sensitivity of the domestic-currency value of any physical or financial asset to unanticipated exchange rate movements. In their work, an asset's currency exposure is estimated by regressing its domestic-currency denominated market return on contemporaneous unanticipated exchange rate movements. As other variables might covary with exchange rate movements and stock returns, omitting them might lead to an overestimation of the proportion of variance attributable to foreign currency movements. Jorion (1990) recommends therefore an augmented market model, described in Equation (4.1), modelling the asset-specific exchange rate sensitivity in excess of the total market's reaction to exchange rate movements.

$$R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + \gamma_i X_{t-k,t} + \varepsilon_{i,t-k,t} \tag{4.1}$$

where $R_{i,t-k,t}$ designates the total return of asset i in period $t-k$ to t, $R_{m,t-k,t}$ the overall stock market return in period $t-k$ to t, β_i asset i's return sensitivity to market risk, $X_{t-k,t}$ the exchange rate factor in period t, γ_i asset i's exposure to the exchange rate independent of the effect these currency movements have on the overall market, and $\varepsilon_{i,t-k,t}$ denotes the white noise error term.

It should be emphasized that, according to Adler and Dumas (1984)'s seminal definition, foreign exchange risk exposure relates to 'unanticipated' changes in exchange rates. Thus in Equation (4.1) stock returns should not fluctuate in response to total exchange rate movements but in response to unexpected exchange rate movements. The rationalization for this specification is that current firm values are assumed to have already incorporated currency fluctuations that were anticipated. Consequently it is only to the extent that exchange rates move by more (or less) than had been expected that they are likely to generate losses and gains in economic value. Notice that by relating firm value to innovations in exchange rate movements rather than to total exchange rate movements, we allow investors to get accustomed to the news contained in exchange rate forecasts and hence to incorporate these forecasts in stock returns. We are moreover in line with Kandil (2015) who shows that 'unanticipated' exchange rate fluctuations are the most relevant shocks that either harm or benefit economic activity and hence impact firm values.

While early foreign exchange risk exposure studies hypothesize that exchange rates are unpredictable and that markets perceive them as truly unpredictable (Jorion, 1990), various approaches have previously been used in the literature to obtain an estimate of unanticipated exchange rate movements. Amihud (1994) recommends the use of an AR(1) model to estimate unanticipated currency movements. After having regressed exchange rate variations on their lagged values, he estimates Equation (4.1) with $X_{t-k,t}$ being defined as the residuals of the AR(1) regression – considering the residuals of the AR(1) regression as unanticipated exchange rate changes. As this procedure only marginally increases the significance of the results, subsequent studies specify the exchange rate factor to be relied on in Equation (4.1) to be orthogonal to fundamental variables, see for instance Gao (2000). More recently, Jongen et al. (2012) compared two alternative ways to build unanticipated movements: using forwards, on the one hand, and using survey information from experts' forecasts, on the other. They conclude that the value-relevance of unanticipated exchange rate movement based on survey-based expectations is the strongest. It should be stressed that the implicit assumption of these studies is that all the information pertaining to these exchange rate expectations is instantaneously and fully incorporated in firms' equity valuation - whatever the statistical properties, the accuracy or reliability of these forecasts. This very strong hypothesis has never been put to the test so far unlike what has been done in other research areas (see for instance Schmeling and Schrimpf, 2011).

Unlike previous studies comparing the value-relevance of total exchange rate movements with the value-impact of unanticipated exchange rate shocks, our objective is to design the most meaningful and relevant exchange rate factor to estimate firms' currency exposure based on the degree to which the information contained in foreign exchange forecasts is incorporated in the stock valuation. Dispersion is inevitably a key ingredient in explaining the variation in markets' responses to these forecasts (Chen et al., 2005). In our research design analyst forecast dispersion proxies the precision of underlying market expectations and, more specifically, the precision of available information to market participants at the moment when the forecasts are disclosed. Given that markets may be more reluctant or may need more time to incorporate the information conveyed through ambiguous or noisy signals compared to the information conveyed through less ambiguous signals, we conjecture that the higher the dispersion, the lower the perceived informational content of disclosed exchange rate expectations and hence the lower their value-relevance for stock markets (Byard and Shaw, 2003) [2]. Across different regimes of disagreement probability, we in-

[2] Our intuition is similar to some extent to Doukas et al. (2006) who, in the context of earnings

vestigate thus how the information contained in exchange rate expectations are differentially incorporated in market prices – and hence how it affects the informational quality of our exchange rate factor candidates. While unanticipated exchange rate movements has appeared so far to be an economically sounder and more reliable exchange rate factor to measure firms' currency exposure (Jongen et al., 2012; Kandil, 2015), we need to assess the value-relevance of unexpected vs. total exchange rate movements across differential levels of disagreement between forecasters.

The empirical investigation is based on the Consensus Economics exchange rate forecasts survey, a highly recognized economic forecast database that is widely disseminated among market participants as well as highly debated in the financial press. We explore to which extent stock prices are exposed to total exchange rate movements - as traditionally measured - and compare this exposure to the valuation impact of revisions in exchange rate forecasts and of unanticipated currency shocks. Unlike previous studies, our main goal is to explain when total exchange rate movements may be considered as poorly performing risk factors to measure firms' currency exposure - in other words when the decomposition of these exchange risk factors in expected and unexpected currency movements enable us to build more reliable and economically more meaningful measures of the forces that are really driving multinationals' stock returns. To accurately assess how investors incorporate publicly disseminated exchange rate forecasts in the stock price valuation process, we analyze the impact of these forecasts and their corresponding unanticipated currency shocks on multinationals' stock price movements both when market participants agree about these forecasts and when their expectations are widely dispersed.

Section 4.2 illustrates the framework we use throughout this paper.

At time t, all the information related to the forecasts formulated at time $t-k$ have already been fully reflected in the price P_t. Hence, what really should influence the price at the point in time is the unanticipated exchange rate movement $(X_{t-k,t} - X^e_{t-k,t})$, i.e.. the difference between the return that was forecast at time $t-k$ for time t, designated by $X^e_{t-k,t}$, and the actual return at time t. This is the reasoning assumed by the literature (Adler and Dumas, 1984; Amihud, 1994; Jongen et al., 2012).

In line with the literature (Frankel and Lee, 1998; Gleason and Lee, 2003), we explore as well the degree to which market prices reflect the information in analysts' forecasts. More specifically we investigate to what extent investors respond

forecasts, modulate the signal content of the forecasts according to its dispersion (at the stock-level) and its sign.

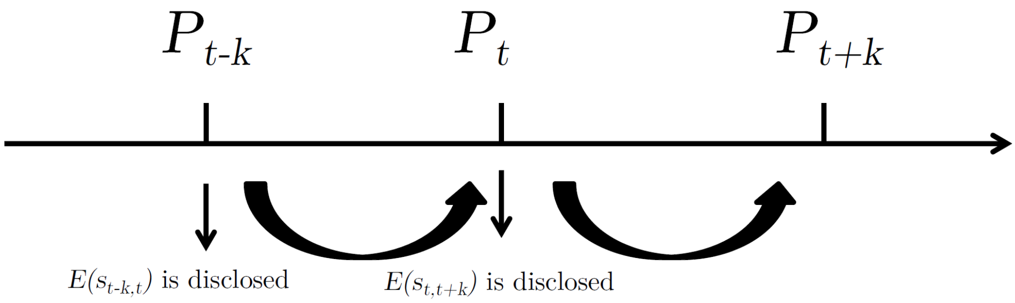

Figure 4.1: Illustration of the price forming process

efficiently to the informational signals contained in forecasts communicated at time t, hence pertaining to time $t + k$ – i.e. to what extent extent they incorporate this information in stock prices at time t. To the extent that forecasts reveal changing market opinions regarding the future evolution of exchange rates, their informational content is assumed to be shared by market participants when it is officially disclosed. It could of course also be the case that the information embedded in the forecast might be somewhat leaked before the official disclosure date. As a consequence, we measure the price impact of this time-variation in market opinions that is expected to culminate in the disclosure at time t of the next period forecast pertaining to time $t + k$.

4.3 Research Design and Sample description

4.3.1 Extension of the model

To put our research questions to the test, we extend the traditional regression approach of Jorion (1990) and estimate herewith the stock value relevance of revisions in expected exchange rate movements as well as unanticipated currency shocks:

$$R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + \gamma_{i1}(X_{t-k,t} - X^e_{t-k,t}) + \gamma_{i2} X^e_{t,t+k} + \varepsilon_{i,t-k,t} \tag{4.2}$$

where γ_{i1} designates the sensitivity to unanticipated movements in the exchange rates, and γ_{i2} the exposure to the next period forecasted return. Both measures rely on expert forecasts, and their perception by market participants. Unanticipated movements are the difference between the forecast communicated at time $t - k$ and the realized exchange rate movement observed at time$t$. The next period forecasted currency return is the expected exchange rate movements over the next period according to the latest exchange rate forecast.

We conjecture that the significance and magnitude of both exposures depend on the perceived relevance of the signal provided by exchange rate forecasts. Following Byard and Shaw (2003) we use the observed heterogeneity across exchange rate anticipations to proxy the relevance of the signal. The underlying rationale is straightforward: when forecasters agree about the future path of currency values, exchange rate expectation data is expected to be perceived as more meaningful and trustworthy by investors. Conversely, when analysts disagree, the signal is most probably regarded as more ambiguous and questionable by market participants. Consequently currency expectations whose dispersion is higher are expected to affect stock markets less strongly and less significantly.[3]

To build a time-varying estimate of the probability that survey analysts are in a state of agreement, the following model is used:

$$\begin{aligned}R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t}& \\ + Prob(S_t = S_1)\gamma_{i1}(X_{t-k,t} - X^e_{t-k,t}) &+ Prob(S_t = S_1)\gamma_{i2}X^e_{t,t+k} \\ + Prob(S_t = S_2)\gamma_{i3}(X_{t-k,t} - X^e_{t-k,t}) &+ Prob(S_t = S_2)\gamma_{i4}X^e_{t,t+k} \\ &+ \varepsilon_{i,t-k,t} \qquad (4.3)\end{aligned}$$

where S is the discrete, unobserved, state variable which takes value 1 in a state we identify as being a state of agreement, and 2 otherwise, i.e. a state of disagreement.

4.3.2 U.S. multinational firms

Our sample is composed of U.S. multinational firms with real operations in Japan and Europe.[4] Due to their real foreign trade and production activities, it can be expected that multinational companies are affected by exchange rate movements. With the help of the Uniworld database of US Multinational Enterprises in Foreign Countries, we have identified 2026 such companies over the period 1999-2011. Of these, we have kept those for which daily stock price information was

[3] Another possible interpretation is that different investors trust different forecasters, and in situations of disagreement, accordingly elaborate different personal expectations regarding the future movements of the exchange rates.

[4] Our focus on this sub-sample of US multinationals is motivated by the fact that Japan and Europe belong to the most important import and export partners of US multinationals, and simultaneously the USD/EUR and the USD/JPY to the most widely and frequently reported and debated exchange rates in financial media.

available from the University of Chicago Center for Research in Security Prices (CRSP) database, for a period of at least 60 months. This process leaves us with a sample of 1675 companies.

Table 4.1 gives an overview of the selected multinationals' geographical dispersion.

Table 4.1: Descriptive Statistics

	#	Europe	Japan
Europe	1148	-	51.05%
Japan	639	91.71%	-
Total Sample	1675	68.54%	38.15%

4.3.3 Exchange risk factors

Every second Monday of each calendar month *Consensus Economics of London* publishes results from a survey among up to 150 leading professional market participants and forecasting agencies for their subjective expectations of a large number of exchange rates. Examples of panel companies include Morgan Stanley, Oxford Economic Forecasting, Deutsche Bank Research and BNP Paribas. The forecasts are point forecasts against the U.S. dollar and are available for various forecast horizons ranging from 1 month to 24 months ahead. We specifically use the 3 and 12 months ahead expectations.

Although the survey participants have a few days time to return their expectations, we know that the vast majority send their forecasts by e-mail on the Friday before the publication day (usually second Monday of the month). We consider this Friday to be the day on which the expectations are formed. On this Friday, we also obtain spot rates data. All spot series are obtained through Datastream and have their origin either in Reuters or Barclays Bank International.

We proceed by defining the natural logarithm of the current spot rate on a particular currency j at time t as $s_{j,t}$ and the natural logarithm of the k-period ahead consensus expectation formed at time t for time $t+k$ as $s^e_{j,t,t+k}$ and make the assumption the expectation corresponds to the unobserved 'true' market observation up to a white noise random error, so that $s^e_{j,t,t+k} = E_t[s_{j,t+k}] + \varepsilon_{j,t+k}$. The k-period realized change in the exchange rate can hence be decomposed into an 'anticipated' (or expected) component and an 'unanticipated' (or noise) component:

$$s_{j,t+k} - s_{j,t} = \underbrace{(s^e_{j,t,t+k} - s_{j,t})}_{\text{anticipated}} + \underbrace{(s_{j,t+k} - s^e_{j,t,t+k})}_{\text{unanticipated}} \tag{4.4}$$

which corresponds to

$$X_{t-k,t} = X^e_{t-k,t} + (X_{t-k,t} - X^e_{t-k,t}) \tag{4.5}$$

in our previous notation.

4.3.4 Probability of agreement among experts

First let us define a measure based on the volatility of the forecasts scaled with respect to the average at time t, as shown in Equation (4.6).

$$\nu_{t,t+k} = \sigma_{t,t+k}/\mu_{t,t+k} \tag{4.6}$$

An overview of the constructed series is presented in Section 4.3.4, and summary statistics are available in Table 4.2.

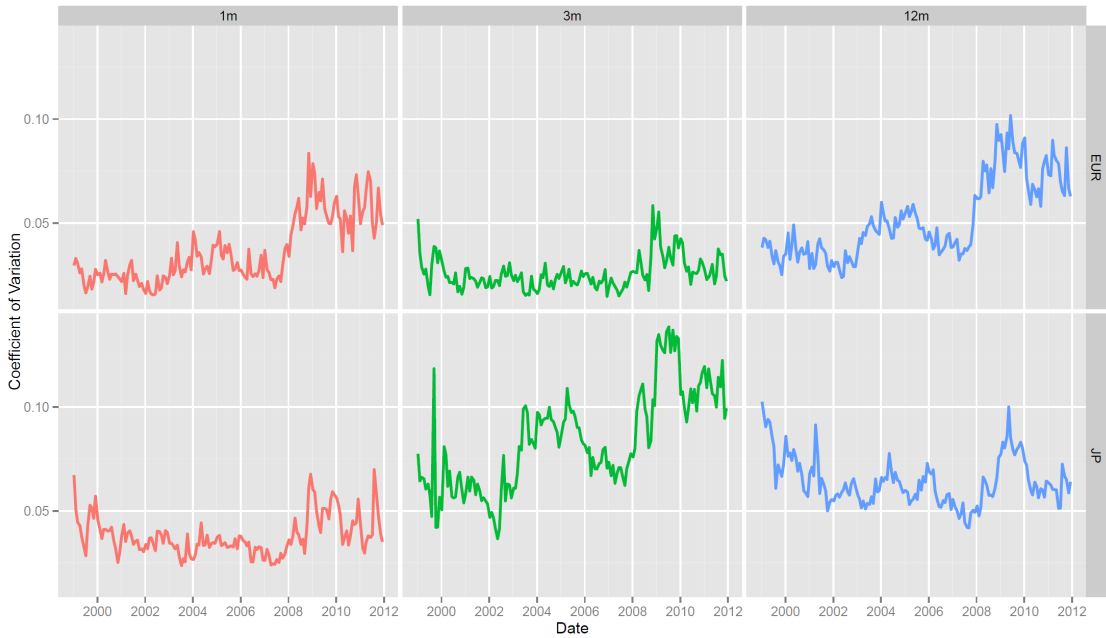

Figure 4.2: Coefficients of variation

To construct a time-varying estimate of the probability of agreement among the forecasters, we use a simple form of regime change model based on a two-state Markov chain, as described in Hamilton (1994).

Our model then takes the following form:

Table 4.2: Summary statistics

		Mean	Median	Min	Max	Std. Dev.	Skew.	Kurt.	J-B	Prob	Obs
Total Return	Europe	-0.09%	0.01%	-9.06%	7.11%	3.21%	-0.21	2.62	2.10	0.2864	155
	Japan	-0.23%	-0.05%	-7.30%	7.93%	3.04%	-0.04	2.72	0.55	0.5000	155
Forecasted Returns	Europe	-0.25%	-0.26%	-3.82%	4.40%	1.53%	0.12	2.78	0.71	0.5000	156
	Japan	-0.07%	-0.35%	-4.14%	4.44%	1.74%	0.21	2.55	2.51	0.2196	156
Unexpected Returns	Europe	0.16%	0.21%	-9.50%	9.22%	3.77%	0.00	2.59	1.09	0.5000	155
	Japan	-0.17%	-0.24%	-8.03%	7.92%	3.28%	-0.01	2.51	1.54	0.3990	155
Coefficient of variation	Europe	3.63%	3.03%	1.54%	8.36%	1.59%	0.91	2.86	21.44	0.0024	156
	Japan	2.59%	2.43%	1.48%	5.84%	0.78%	1.52	6.01	119.13	0.0010	156
3-Month forecast horizon											
Total Return	Europe	-0.37%	-0.79%	-10.25%	16.38%	5.58%	0.49	2.84	6.18	0.0413	153
	Japan	-0.79%	-0.33%	-14.54%	11.47%	4.87%	-0.07	2.91	0.19	0.5000	153
Forecasted Returns	Europe	-0.74%	-0.73%	-6.98%	5.74%	2.32%	-0.12	3.08	0.44	0.5000	156
	Japan	-0.07%	-0.27%	-5.68%	6.48%	2.64%	0.00	2.44	2.02	0.3016	156
Unexpected Returns	Europe	0.44%	-0.26%	-14.52%	17.50%	6.33%	0.33	2.49	4.45	0.0783	153
	Japan	-0.73%	-0.43%	-16.08%	12.40%	5.74%	-0.12	2.62	1.28	0.4712	153
Coefficient of variation	Europe	5.16%	4.56%	2.38%	10.17%	1.91%	0.73	2.45	15.73	0.0054	156
	Japan	3.82%	3.59%	2.38%	6.99%	0.94%	1.13	4.19	42.64	0.0010	156
12-month forecast horizon											
Total Return	Europe	-2.16%	-3.71%	-23.11%	20.05%	10.83%	0.19	2.06	6.15	0.0417	144
	Japan	-2.93%	-4.45%	-19.32%	16.22%	8.59%	0.38	2.27	6.67	0.0356	144
Forecasted Returns	Europe	-2.13%	-1.82%	-16.32%	9.06%	5.02%	-0.41	3.10	4.33	0.0830	156
	Japan	-0.25%	-0.08%	-10.59%	9.92%	5.42%	-0.02	2.19	4.27	0.0850	156
Unexpected Returns	Europe	0.22%	-1.93%	-19.97%	28.32%	11.72%	0.38	2.41	5.60	0.0497	144
	Japan	-2.18%	-4.52%	-20.68%	19.12%	11.36%	0.29	1.78	10.90	0.0129	144
Coefficient of variation	Europe	8.41%	8.08%	3.67%	13.86%	2.41%	0.31	2.33	5.51	0.0517	156
	Japan	6.42%	6.16%	4.19%	10.26%	1.17%	0.94	3.78	26.80	0.0013	156

$$\nu_{t,t+k} = \mu_1 + \varepsilon_t \quad \text{for State 1} \tag{4.7}$$
$$\nu_{t,t+k} = \mu_2 + \varepsilon_t \quad \text{for State 2} \tag{4.8}$$

where:

$$\varepsilon_t \sim (0, \sigma_1^2) \quad \text{for State 1} \tag{4.9}$$
$$\varepsilon_t \sim (0, \sigma_2^2) \quad \text{for State 2} \tag{4.10}$$

The model is estimated using Maximum Likelihood.[5] As an example, Figure 4.3 shows the coefficient of variation in the case of the 3-month horizon for Europe. By visually comparing this graph with Section 4.3.4, we identify the first state as being a state of agreement, i.e. with comparatively lower values for the coefficient of variation (measuring the dispersion in forecasts). Figure 4.3 reveals that the state of agreement is followed by a period of roughly 20 months of probable disagreement, then by a slightly shorter period of probable agreement. The series end with a highly probable disagreement period. The interpretation is coherent with observed patterns in Section 4.3.4.

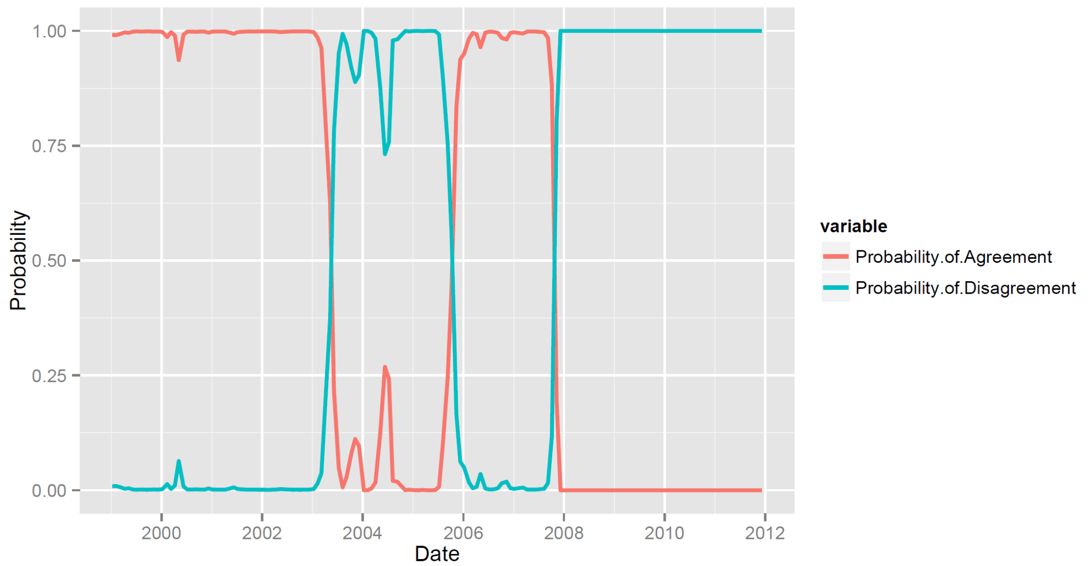

Figure 4.3: Example of regime switching for the 3-month EUR coefficient of variation

[5] The maximization of the log-likelihood function is carried out with the help of the Expectation Maximization (EM) Algorithm. We use MATLAB for all computations, and more specifically in this case, a modified version of the package created by Perlin (2012)

4.4 Empirical Findings

Table 4.3 shows the impact of total exchange rate variations versus disaggregated variations. To establish a benchmark, the upper part of the table uses the traditional currency risk exposure specification using a market risk factor based on the CRSP value weighted market returns series (which we will refer to as market returns from now on) and a currency risk factor based on the total realized exchange rate return observed on the previous period. For each risk factor the proportion of firms that is statistically significantly exposed to the risk factor (at the chosen level of $\alpha = 0.05$) is provided. It should be emphasized that reported regressions investigate US multinational firms' currency exposures to the euro and to the Japanese yen.[6]

Firms documenting significant currency exposure range from 9.6% to 66.7% of their corresponding sample in contrast with previous results. Jorion (1990), for instance, finds that only 5% of 287 U.S. multinational corporations exhibit significant exchange risk exposure, whereas Choi and Prasad (1995) find that 15% of 409 multinationals are significantly exposed. Bartram and Bodnar (2012), who study all non-financial firms and thus do not restrict their analysis to multinational firms, obtain a fraction of significant coefficients of 11.4% across 37 countries. At this stage, possible explanations for our results include the fact that unlike most other studies, we do not rely on a basket of currencies to build our foreign exchange factors. Our database allows us to assess which multinationals have foreign operations in which countries. This enables us on the one hand to rely on currency factors that are specific to firms' foreign activities, and, on the other hand, to restrict our analysis to firms that are more likely to be affected by movements in these selected currencies. On the top of that we do not exclusively investigate currency exposure at the 1-month observation frequency, as typically explored in the literature, but as well at the 3- and 12-month frequency.

The lower part of the table refers to the model presented in Equation (4.2). We disaggregate the exposure to realized total currency movements into exposures to expected and unexpected exchange rate movement components. In accordance with theoretical groundings, the exposure to unexpected currency movements is measured based on $(X_{t-k,t} - X^e_{t-k,t})$, the difference between the return forecasted at time $t-k$ for time t, designated by $X^e_{t-k,t}$, and the ex post observed return $X_{t-k,t}$ at time t. Additionally, we also aim to verify to which extent forecasts about future exchange rate movements affect firms' stock values. Results examining both components separately reveal that they have significant impacts

[6] Each of these regressions is performed using 1-, 3- and 12-month currency forecasts.

Table 4.3: The impact of total exchange rate variations *versus* disaggregated variations

The table reports, for $k = 1$, 3, and 12 months, cross-sectional summary statistics of the estimation of the following regression models. The first is $R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + \gamma_i X_{t-k,t} + \varepsilon_{i,t-k,t}$, where $R_{i,t-k,t}$ designates the total return of asset i over period $t-k$ to t, $R_{m,t-k,t}$ the overall stock market return in period $t-k$ to t, β_i asset i's return sensitivity to market risk, $X_{t-k,t}$ the total return over period $t-k$ to t, γ_i asset i's exposure to the exchange rate independent of the effect these currency movements have on the overall market, and $\varepsilon_{i,t-k,t}$ denotes the white noise error term. The second is $R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + \gamma_{i1}(X_{t-k,t} - X^e_{t-k,t}) + \gamma_{i2} X^e_{t,t+k} + \varepsilon_{i,t-k,t}$ which corresponds to Eq. (4.2) in the text, where $(X_{t-k,t} - X^e_{t-k,t})$ denotes the unanticipated return over the period $t-k$ to t, and $X^e_{t,t+k}$ represents the forecasted return, over the period t to $t+k$, based on the forecast communicated at time t.

	EUR			JP		
	1m	3m	12m	1m	3m	12m
Constant	5.4	24.5	61.9	5.3	25.7	63.9
Market	97.7	95.0	92.8	98.6	97.5	96.1
$\boldsymbol{X_{t-k,t}}$	**14.9**	**31.9**	**60.6**	**9.6**	**26.5**	**66.7**
of which positive	*42.9*	*54.0*	*50.4*	*41.0*	*61.6*	*57.2*
of which negative	*57.1*	*46.0*	*49.6*	*59.0*	*38.4*	*42.8*
Adj R^2	28.5	30.5	40.4	30.7	33.1	43.8
Constant	4.8	24.2	61.7	5.7	28.1	66.1
Market	97.8	95.1	93.5	98.6	97.6	96.5
$X^e_{t,t+k}$	8.5	17.2	45.9	10.8	31.7	59.7
of which positive	*49.5*	*36.5*	*39.8*	*88.4*	*86.6*	*65.8*
of which negative	*50.5*	*63.5*	*60.2*	*11.6*	*13.4*	*34.2*
$X_{t-k,t} - X^e_{t-k,t}$	12.9	28.6	47.9	8.8	39.9	70.5
of which positive	*56.1*	*55.4*	*53.5*	*71.4*	*78.0*	*61.5*
of which negative	*43.9*	*44.6*	*46.5*	*28.6*	*22.0*	*38.5*
of firms with significant FX factor	**17.1**	**39.2**	**68.4**	**15.2**	**52.4**	**78.8**
of which positive	*54.8*	*49.2*	*47.8*	*82.0*	*79.0*	*61.5*
of which negative	*45.2*	*50.8*	*52.2*	*18.0*	*21.0*	*38.5*
Adj R^2	28.6	31.0	43.5	30.8	34.4	48.7

Numbers represent the percentage of firms for which the coefficient on the independent variable shows significance at the $\alpha = 0.05$ level, except for the Adj R^2 line, which shows the average Adjusted R^2 obtained for the whole number of regressions.

on multinational firm values. Their influence is even complementary as, when considering both components together, we obtain larger proportions of firms that are significantly exposed. Increases with respect to previous specification vary from 2.2% to 25.9% in the case of the 3-month horizon for the Japanese region.

Table 4.5: How disagreement among forecasters affects the impact of Expected Returns

The table reports, for k = 1, 3, and 12 months, cross-sectional summary statistics of the estimation of the following regression models. The first is

$$R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + \gamma_i X^e_{t,t+k} + \varepsilon_{i,t-k,t}$$

where $R_{i,t-k,t}$ designates the total return of asset i over period $t-k$ to t, $R_{m,t-k,t}$ the overall stock market return in period $t-k$ to t, β_i asset i's return sensitivity to market risk, $X^e_{t,t+k}$ forecasted return over period tk to $t+k$, γ_i asset i's exposure to the forecasted return independent of the effect these have on the overall market, and $\varepsilon_{i,t-k,t}$ denotes the white noise error term.
The second is

$$R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + Prob(S_t = S_1)\gamma_{i1} X^e_{t,t+k} + Prob(S_t = S_2)\gamma_{i2} X^e_{t,t+k} + \varepsilon_{i,t-k,t}$$

where $X^e_{t,t+k}$ represents the forecasted return, over the period t to $t+k$, based on the forecast communicated at time t, and where S is the discrete, unobserved, state variable which takes value 1 in a state we identify as being a state of agreement, and 2 otherwise, i.e. a state of disagreement.

	EUR			JP		
	1m	3m	12m	1m	3m	12m
Constant	4.6	24.1	60.9	4.9	24.6	59.7
Market	97.7	96.9	93.9	98.6	98.0	96.5
$X^e_{t,t+k}$	9.0	18.7	57.8	10.4	19.3	46.3
Adj R^2	28.2	29.9	40.4	30.7	32.7	41.3
Constant	3.8	24.5	60.9	5.0	23.9	60.0
Market	97.6	96.8	94.2	98.6	98.0	96.5
$X^e_{t,t+k}$ in agreement regime	4.8	18.5	56.3	10.2	16.5	46.6
$X^e_{t,t+k}$ in disagreement regime	8.1	6.4	38.2	8.6	5.5	5.7
of firms with significant expected FX factor	**12.5**	**23.7**	**73.9**	**17.7**	**20.7**	**49.6**
Adj R^2	28.2	30.0	42.2	30.8	32.7	41.4

Numbers represent the percentage of firms for which the coefficient on the independent variable shows significance at the $\alpha = 0.05$ level, except for the Adj R^2 line, which shows the average Adjusted R^2 obtained for the whole number of regressions.

Table 4.5 and Table 4.7 display the empirical findings regarding the impact of these two complementary currency factors, i.e. forecasts about the future movements in exchange rates and unanticipated currency movements, measured as the difference between the currency returns forecasted at time $t-k$ for time t and the actual exchange rate returns observed at time t. In each table we suggest to investigate the impact on firm value across two distinctive regimes: regime 1 characterized by a low dispersion in these currency forecasts and regime 2 characterized by a high dispersion, hence a strong disagreement between forecasters.

We observe that in both cases, distinguishing between the two regimes provides a better fit to the return data, as measured by the Adjusted R^2. More stock

Table 4.7: How disagreement among forecasters affects the impact of Unexpected Returns

The table reports, for k = 1, 3, and 12 months, cross-sectional summary statistics of the estimation of the following regression models. The first is

$$R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + \gamma_{i1}(X_{t-k,t} - X^e_{t-k,t}) + \varepsilon_{i,t-k,t}$$

where $R_{i,t-k,t}$ designates the total return of asset i over period $t-k$ to t, $R_{m,t-k,t}$ the overall stock market return in period $t-k$ to t, β_i asset i's return sensitivity to market risk, where $(X_{t-k,t} - X^e_{t-k,t})$ denotes the unanticipated return over the period $t-k$ to t, and $\varepsilon_{i,t-k,t}$ denotes the white noise error term.
The second is

$$R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + Prob(S_t = S_1)\gamma_{i1}(X_{t-k,t} - X^e_{t-k,t}) + Prob(S_t = S_2)\gamma_{i2}(X_{t-k,t} - X^e_{t-k,t}) + \varepsilon_{i,t-k,t}$$

where S is the discrete, unobserved, state variable which takes value 1 in a state we identify as being a state of agreement, and 2 otherwise, i.e. a state of disagreement.

	EUR			JP		
	1m	3m	12m	1m	3m	12m
Constant	4.8	27.3	62.8	5.8	25.4	63.6
Market	97.8	95.4	93.4	98.6	97.8	96.2
$X_{t-k,t} - X^e_{t-k,t}$	14.0	29.4	58.4	8.3	32.2	65.5
Adj R^2	28.4	30.4	40.5	30.6	33.3	43.9
Constant	4.5	27.4	63.5	6.0	25.6	63.0
Market	97.6	95.7	93.7	98.6	97.6	96.4
$X_{t-k,t} - X^e_{t-k,t}$ in agreement regime	9.5	29.0	56.9	8.9	32.3	65.0
$X_{t-k,t} - X^e_{t-k,t}$ in disagreement regime	9.5	15.1	20.9	9.6	16.3	9.4
of firms with significant unexpected FX factor	**18.4**	**39.6**	**66.5**	**17.4**	**42.9**	**69.4**
Adj R^2	28.5	30.9	41.3	30.8	33.8	44.1

Numbers represent the percentage of firms for which the coefficient on the independent variable shows significance at the $\alpha = 0.05$ level, except for the Adj R^2 line, which shows the average Adjusted R^2 obtained for the whole number of regressions.

values are found to be significantly exposed to forecasted (Table 4.5)and unanticipated (Table 4.7) exchange rate movements when we take into account the discrimination between agreement and disagreement regimes. Most importantly, in both tables, empirical findings reveal that stock values react deferentially to these exchange risk factors in agreement vs. disagreement regimes. Both disaggregated exchange risk factor components turn out to be substantially more value-relevant in agreement regimes than in disagreement regimes. When comparing both regimes, we observe an average increase of 20.6% of significantly exposed firm values to exchange rate forecasts in agreement vs. disagreement regimes, and an average increase of 30.4% of significantly exposed firm values to unanticipated exchange rate fluctuations.[7] These empirical results support the intuition that forecasts are perceived by investors as carrying more information when experts agree about the future path of exchange rates, than when forecasters seem unable to agree on the future evolution of currencies.

Table 4.9 shows our results for the complete model presented in Equation (4.3). To allow for an easier comparison, we reproduce the upper part of Table 4.3 in the upper part of Table 4.9.

First of all we see that the complete model is the one best able to explain the data, as the Adjusted R^2 obtained are the largest in this setting, with values ranging from 28.7% for the 1-month horizon in Europe to 49.1% for the 12-month horizon in Japan. The improvement is noticeable on a more standard framework, such as the one presented in the top of table, which corresponds to the traditional setting used in the literature to measure firms' currency exposures.

We also see additional support for our previously documented finding that investors pay more attention to forecasts when experts are in agreement, with an average of 30.6% more firms being significantly exposed to disaggregated foreign exchange factors in the agreement regime. As theory and intuition would predict, widely diverging forecasts are considered less reliable by investors. The disaggregation of exchange rates based on widely diverging forecasts doesn't correspond hence to investors' information perception of exchange rate risk. When forecasters have strongly contradictory opinions about the future, investors don't rely on the signal forecasters send to the market but rely on market observed exchange rate movements. This is illustrated for instance by the drop from 66.7% of significantly exposed firms to the total Japanese exchange rate risk factor to 18.5% of significantly exposed firms to the forecast-based disaggregated exchange risk factor in disagreement regime for the 12-month horizon in Japan. In contrast, when forecasters share common opinions about future exchange rate movements,

[7] With an exception for the European region at the 1-month horizon.

Table 4.9: Complete model with agreement regimes

The table reports, for k = 1, 3, and 12 months, cross-sectional summary statistics of the estimation of the following regression models. The first is

$$R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} + \gamma_i X_{t-k,t} + \varepsilon_{i,t-k,t}$$

where $R_{i,t-k,t}$ designates the total return of asset i over period $t-k$ to t, $R_{m,t-k,t}$ the overall stock market return in period $t-k$ to t, β_i asset i's return sensitivity to market risk, $X_{t-k,t}$ the total return over period $t-k$ to t, γ_i asset i's exposure to the exchange rate independent of the effect these currency movements have on the overall market, and $\varepsilon_{i,t-k,t}$ denotes the white noise error term.
The second is

$$\begin{aligned} R_{i,t-k,t} = \alpha_i + \beta_i R_{m,t-k,t} &+ Prob(S_t = S_1)\gamma_{i1}(X_{t-k,t} - X^e_{t-k,t}) + Prob(S_t = S_1)\gamma_{i2} X^e_{t,t+k} \\ &+ Prob(S_t = S_2)\gamma_{i3}(X_{t-k,t} - X^e_{t-k,t}) + Prob(S_t = S_2)\gamma_{i4} X^e_{t,t+k} + \varepsilon_{i,t-k,t} \end{aligned}$$

which corresponds to Eq. (4.3) in the text, where S is the discrete, unobserved, state variable which takes value 1 in a state we identify as being a state of agreement, and 2 otherwise, i.e. a state of disagreement.

	EUR			JP		
	1m	3m	12m	1m	3m	12m
Constant	5.4	24.5	61.9	5.3	25.7	63.9
Market	97.7	95.0	92.8	98.6	97.5	96.1
$\boldsymbol{X_{t-k,t}}$	**14.9**	**31.9**	**60.6**	**9.6**	**26.5**	**66.7**
of which positive	*42.9*	*54.0*	*50.4*	*41.0*	*61.6*	*57.2*
of which negative	*57.1*	*46.0*	*49.6*	*59.0*	*38.4*	*42.8*
Adj R^2	28.5	30.5	40.4	30.7	33.1	43.8
Constant	4.0	24.9	61.5	5.3	27.6	64.7
Market	96.9	95.6	93.7	98.4	97.6	96.4
$X^e_{t,t+k}$ in agreement regime	7.5	16.5	46.2	11.1	29.7	59.8
of which positive	*22.1*	*38.6*	*42.2*	*85.9*	*86.2*	*65.9*
of which negative	*77.9*	*61.4*	*57.8*	*14.1*	*13.8*	*34.1*
$X^e_{t,t+k}$ in disagreement regime	7.9	6.6	39.6	3.8	6.0	8.9
of which positive	*73.3*	*55.3*	*33.6*	*33.3*	*73.7*	*57.9*
of which negative	*26.7*	*44.7*	*66.4*	*66.7*	*26.3*	*42.1*
$X_{t-k,t} - X^e_{t-k,t}$ in agreement regime	12.5	28.8	47.4	10.2	40.2	70.3
of which positive	*18.9*	*59.6*	*51.3*	*73.8*	*78.5*	*61.2*
of which negative	*81.1*	*40.4*	*48.7*	*26.2*	*21.5*	*38.8*
$X_{t-k,t} - X^e_{t-k,t}$ in disagreement regime	9.6	15.4	21.9	4.2	17.7	11.1
of which positive	*79.1*	*15.9*	*36.0*	*33.3*	*16.8*	*54.9*
of which negative	*20.9*	*84.1*	*64.0*	*66.7*	*83.2*	*45.1*
of firms with significant factor in agreement regime	14.5	38.7	67.8	16.2	51.6	79.0
of which positive	*20.5*	*51.0*	*48.4*	*80.1*	*80.1*	*61.2*
of which negative	*79.5*	*49.0*	*51.6*	*19.9*	*19.9*	*38.8*
of firms with significant factor in disagreement regime	13.4	20.9	53.2	4.4	22.3	18.5
of which positive	*74.2*	*37.4*	*38.0*	*35.7*	*40.8*	*59.7*
of which negative	*25.8*	*62.6*	*62.0*	*64.3*	*59.2*	*40.3*
of firms with significant FX factor	**26.3**	**51.4**	**85.2**	**19.0**	**62.2**	**82.7**
of which positive	*47.8*	*45.2*	*44.0*	*55.6*	*61.4*	*58.1*
of which negative	*52.2*	*54.8*	*56.0*	*44.4*	*38.6*	*41.9*
Adj R^2	28.7	31.6	46.0	30.9	35.0	49.1

Numbers represent the percentage of firms for which the coefficient on the independent variable shows significance at the $\alpha = 0.05$ level, except for the Adj R^2 line, which shows the average Adjusted R^2 obtained for the whole number of regressions.

the most value-relevant informational signals affecting companies' stock values are currency forecasts and the extent to which observed market exchange rate movements diverge from previously disclosed forecasts. In these regimes characterized by convergent opinions about future exchange rate movements, more than 50% (80%) of US multinationals firms are significantly affected by our disaggregated exchange risk factors when considering 3 and 12-month forecasts. The comparison between empirical findings obtained using the traditional approach to estimate firms' currency exposure with these results using the disaggregated exchange risk factor approach (see columns 2, 3, 5 and 6) reveals that when forecasters have convergent views about the future path of exchange rates, more firms are significantly exposed to these forecasts and the degree to which they diverge from ex post observed exchange rate fluctuations. The proportion of firms that is documented significantly sensitive to currency movements using our modified approach is, hence, under these circumstances, much higher than the percentage of firms considered as significantly exposed to exchange rate movements using the traditional exchange risk factor. This emphasizes the importance of including the investigation of firms' sensitivity to exchange rate forecasts and to unanticipated exchange rate movements as well as the importance of discriminating between periods in which investors lend more credit to forecasts from situations in which they do less. Our results offer hereby a more informed and nuanced understanding of the role of exchange rate forecasts when estimating firms' exposure to currency movements.

4.5 Concluding Remarks

We consider the exposure of U.S. multinationals to exchange rate movements. While recognizing the importance of using unanticipated movements to explain stock returns, we show that the use of the information contained in next period forecasts proves fruitful as well. Most importantly, we construct a time-varying measure of the probability that forecasters are in a situation of agreement vs. disagreement – a measure that enables us to shed new, more nuanced, light on the role of currency forecasts in the estimation of firms' currency exposures. Our agreement vs. disagreement regimes allow us to test whether markets respond deferentially to experts' opinions according to the level of dispersion among experts' forecasts. While our empirical findings stress once more that being able to identify the regions in which each multinational has foreign operations - allowing us to measure firms' currency exposure to specific currencies rather than a weighted basket, increases the precision and significance of exposure estimates, the two main findings of this paper are: (1) Taking into account exchange rate forecasts together with unanticipated movements lead to statistically stronger and more meaningful currency exposure estimates. (2) The value-relevance of exchange rate risk factors constructed based on forecast information varies with the degree of agreement among panel experts. Our findings reveal that when forecasters' opinions converge, the investigation of firm values' sensitivity to exchange rate forecasts and to unanticipated currency movements generates economically relevant and intuitive information regarding firms' currency exposures. They reveal furthermore the importance of discriminating between periods in which forecasters share common views about future exchange rate movements from periods in which opinions diverge: results show that when cracks appear in forecasters' crystal balls, investors feel less inclined to lend credence to their predictions – and hence to take them into account in their perception of firms' currency exposures.

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Part IV

Conclusions and Suggestions for Future Research

Chapter 5

Conclusion

5.1 Conclusive remarks

The conceptual beauty of theoretical models does not always meet reality in the nicest way. Some of the most famous predictions in finance have also been the hardest to reconcile with empirical investigations. The CAPM of Sharpe (1964) and Lintner (1965) is one of most widely used benchmarks in finance, still extensively used by finance practitioners in professional environments to this day, and at the same time, it is the object of one of the longest-lasting debate in finance.

In a world of beautiful people in beautiful markets, i.e., rational agents, who update their beliefs according to Bayes' law, and have preferences characterized by intertemporal utility maximization, who trade in complete, liquid, efficient and competitive markets, one of the predictions of the CAPM is that the beta of a stock should give us all the information we need about its risk, and accordingly, its expected return. There have been many proposed refinements to what might some consider its excessively simple design, but none have gained such prominence as to eclipse the influence of the CAPM.

In time, it is unavoidable that empirical investigations will bring to light elements conflicting with the expectations set by the classical framework. In this thesis, we respectfully think we have found an interesting pattern that conflicts with theoretical expectations about the connection between measures of risk and return on the one hand, and market-wide measures of disagreement on the other. In Chapter 2 and Chapter 3, we have shown how disagreement induces an effect on the average excess returns of portfolios constructed on the basis of cash flow and discount rate betas.

While we do not pretend to be able to discern among all possible explanations for this phenomenon, we argue that this seems to be a mispricing consistent with Miller (1977)'s conjecture that, in a market in which there is little to no short-selling, the price signal is carried by the investors who hold the highest valuation of the asset. We have observed that stock-level disagreement increases with our measures of risk, and decidedly so in periods of higher disagreement. With divergence of opinion being then higher for those assets, their price will be overvalued, and their returns substantially lower. This is exactly what we observe in our data. Our results also agree with previous results from Baker et al. (2011); Frazzini and Pedersen (2014); Antoniou et al. (2016).

We remain aware, as Baker and Wurgler (2006), of the fact that these patterns might actually not be mispricings at all, and merely reflect compensation for systematic risk, which our analysis was not able to discover. There are also other competing interpretations. Dispersion of forecasts could denote uncertainty about future outcomes. Nevertheless, we think our results do not support the interpretation of disagreement being a priced risk factor, even though we acknowledge that firmly establishing this requires a methodological framework we have not implemented.

There might also be other reasons for observing lower returns, for portfolios with high cash flow and discount rate beta, in high periods of disagreement. What we observe may simply be a manifestation of another market-wide mood indicator, sentiment. In Chapter 3, we have proposed to put that hypothesis under scrutiny. Our results suggest that, while sentiment does play a decisive role in affecting the risk return relationships of our portfolios, this effect is particularly strong in periods of high disagreement. Far from being sidelined by the level of market sentiment, our market-wide measure of disagreement actually appears to work best in tandem with it. Moreover, it appears that leveraging the information lying in our market-wide disagreement measure provides key additional insights, a result which appears consistent with Stambaugh et al. (2012), who find that "If the primary form of mispricing is overpricing, then mispricing should be more prevalent when sentiment is high".

Another possibility would be that it is not disagreement that influences the risk return relationship, and that the real cause is due to another effect we have missed. While it is impossible to completely rule out this possibility, we gain some assurance from the robustness checks we have performed in Section 2.3.4, which show our results holding their ground when we use different time series of disagreement.

Finally, we bring our attention to foreign exchange exposure in Chapter 4. That multinational companies should be exposed to foreign exchange risk is a firmly grounded theory in the literature (Shapiro, 1975; Dumas, 1978; Hodder, 1982; Levi, 1994; Bodnar et al., 2002), but this exposure has proven to be elusive in the data (Jorion, 1990; He and Ng, 1998; Griffin and Stulz, 2001). Our results tend to confirm that, in agreement with Adler and Dumas (1984), it matters to consider unexpected returns to capture exchange risk exposure. They also show that being able to modulate the signal on the basis of the level of dispersion in the forecasts, and thus discriminate between periods when forecasters share common views about future movements from periods when their opinions diverge, is essential to capture the exposure of firms to foreign exchange risk.

Two main insights appear in our investigation. (i) Disagreement, when incorporated in the analysis as a market-wide indicator, allows us to better understand the relationship between risk and returns. This additional information is complementary to the one provided by the indicator of sentiment, already identified in the extant literature. (ii) Being able to disentangle a stock's beta into its cash flow and discount rate betas enables us to to capture effects that are not apparent otherwise.

5.2 Future research

5.2.1 Methodological framework to investigate economic significance

At this stage, our analysis suffers from being unable to provide some decisive information about the economical significance of the observed phenomenons. We think our findings point the way to relevant research areas, in which other formal methodological tools can be employed. In Buraschi et al. (2014a), for instance, the authors use a three-step treatment of their disagreement measure: in a first step, they follow Ang et al. (2006) and construct factor mimicking portfolios for their untraded disagreement proxy. They then regress the time series of portfolio returns on the factor mimicking portfolio returns, and the two Fama-French factors. In a last step they regress the average excess return on the vector of estimated factor exposures. Their procedure allows them to draw conclusions as to the market price of their disagreement proxy.

5.2.2 Assessing the strength of prevailing limits to arbitrage

Part of our analysis relies on limits to arbitrage binding the behavior of certain investors. Therefore, our work would benefit from leveraging approach to objectively assess the prevailing strength of limits to arbitrage. For instance, Chen et al. (2002) use breadth of ownership to signal a tightness in short-sale constraints.

5.2.3 Refinement of the disagreement measure

Quite simply, our analysis would benefit greatly from being replicated and enhanced using the analysts forecasts information from the reference I/B/E/S database.

First of all, it would allow us to be much more confident that our results are not due to some particularities of our database. Given that I/B/E/S has been extensively used by finance practitioners, certain database-specific best practices in terms of data manipulation have become necessary standards for published research.

It presents some specificities that would allow to leverage possible improvements in the construction of disagreement measures. Lahiri and Sheng (2010), for instance, propose to use the quasi-standard deviation or inter-quartile range instead of the standard deviation of forecasts, which is particularly susceptible to the presence of outliers in the sample. Doing so requires having access to individual point estimates of the forecasts, something that was technically not possible using the Capital IQ database.

Our analysis would greatly benefit from being able to leverage longer time-series in the definition of our market-wide disagreement measure. Doing so would allow us to be more confident that our results are not period-specific.

Another added benefit from being able to widen the period under consideration lies in the fact that the decomposition of returns methodology, which we use to obtain our cash flow and discount rate betas, also tends to benefit from being applied to larger time intervals. In Campbell and Vuolteenaho (2004), the author compare their results for two time periods of more than 30 years: 1929-1963 and 1963-2001. In more recent empirical implementations, the time frame are larger than 30 years (Botshekan et al., 2012; Garrett and Priestley, 2012).

Part V

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