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Three Essays on the Impact of Analysts on Financial Markets

Farhat, Amel

UNIVERSITY OF CALGARY

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by

Amel Farhat

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Abstract

This thesis studies three different topics on the impact of analysts on financial markets.

The first chapter documents that the price of analysts' dispersion risk in the cross-section of stock returns changes over time, in particular, turns positive in periods of high analyst dispersion. Our result holds using 100 test portfolios that are double-sorted on their betas and their coefficients on aggregate dispersion, as well as numerous test portfolios. We construct a general equilibrium model in the spirit of Merton's ICAPM, in which analysts of different types have heterogeneous beliefs and provide different forecasts of a macroeconomic factor. The consumer does not trust either analyst fully, and dynamically adjusts the weight given to each analyst, given the history of their past forecast performance. In equilibrium, each asset's risk premium depends on its exposure to three factors: the market portfolio, the macroeconomic factor, and, a "flight-to-safety" factor. The first term increases with dispersion, while the third term declines. The latter decline occurs because consumers shift into assets with lower cash flow betas during periods of high dispersion. The model provides a testable implication that the changing sign of the price of risk is due to the flight-to-safety during periods of high dispersion. We find strong support for such a flight to safety in the data.

The second chapter questions the view that all analysts are equal and develop the idea that analysts may have different strategic behaviour to influence the market. The main contribution is to provide evidence that the market assigns different weights to different analysts and to show that more experienced analysts have more significant impact on asset prices and trading activity.

The third chapter studies the relation between dispersion, short sale constraints, and stock returns. The main contribution is to analyze the high returns of a portfolio formed by unconstrained and low opinion divergence stocks. Such portfolio contains stocks with low total and idiosyncratic risks and low leverage. Three and four factors models, as well as liquidity factors models, cannot account for these high abnormal returns.

Preface

Chapter 1 of this thesis is a working paper with Professor Alexander David entitled "When is the Price of Dispersion Risk Positive?"I was responsible for data collection and empirical factor analysis. Professor Alexander David developed the production economy N-asset general equilibrium model.

The remaining parts are my original work. No part of this thesis has been previously published.

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To Sophia and Kenza, the greatest joy of my life...

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Chapter 1

Introduction

The role of analysts in the capital market has gained substantial interest over the past several decades. As a result, a large number of academic studies aim to understand how analysts' forecasts affect stock prices and returns. This thesis studies three different topics on the impact of analysts on financial markets.

We focus on dispersion in the first chapter, where we examine the asset pricing implications of dispersion in investors' beliefs. The contribution of the first chapter is to show that the price of dispersion risk is time-varying in the cross-section, and potentially provides a resolution to the different views on the sign. Empirically, we find that in the cross-section of stock returns, aggregate dispersion is negatively priced in low dispersion months and positively priced in high dispersion months. To study the effects of aggregate dispersion on the cross-section of stock returns, we run tow-stage regression à la Fama and MacBeth (1973) on the 100 β-δ portfolios. We show that the price of dispersion risk is negative in low dispersion months (-6.067%, t-statistic $= -4.52$) and positive in high dispersion months (24.92%, t-statistic $= 4.67$). The price of dispersion risk is statistically insignificant using the full sample period or medium-dispersion months. We next show that our finding is robust to the choice of test portfolios, as it holds using a variety of portfolios obtained from the website of Ken French.

To understand the changing sign of the price of dispersion risk, we construct a production economy N-asset general equilibrium model in the spirit of Merton's ICAPM[1], in which analysts of different types have heterogeneous beliefs and provide different forecasts of a macroeconomic factor (aggregate earnings growth). The consumer does not trust either analyst fully, and dynamically adjusts the weight given to each analyst, given the history of their past forecast performance. The beliefs of each analyst and the weight the consumer assigns to each analyst's forecast, become state variables in the ICAPM framework whose shifts the consumer hedges against. We derive an equilibrium cross-sectional pricing equation for our model where we find three terms in each asset's risk premium.

The second chapter of the thesis explores the individual characteristics of analysts. In particular, this chapter concentrates on analysts' experience. This idea is motivated by the model described in the previous chapter, where the consumer does not fully trust any particular analyst and adjusts the weight given to each analyst, given the history of their past forecast performance. The main contribution of this chapter is to provide evidence that the market assigns different weights to different analysts and to show that more experienced analysts have more significant impact on asset prices and trading activity.

Empirically, I observe that the frequency of small positive forecast errors is larger than the frequency of small negative forecast errors for experienced analysts. I do not detect this characteristic for inexperienced analysts. Second, I show that firms followed by experienced analysts display a more pronounced post-earning announcement drift and a higher trading activity than firms followed by inexperienced analysts. Combining these two empirical facts, I infer that experienced analysts know how to impact the market. They do so by adjusting their forecasts, which allow them to surprise the market and generate more trades.

The third chapter focuses on the dispersion of analysts' forecasts and presents an analysis of the interaction between dispersion in analysts' forecasts and short sale constraints, measured by the short interest ratio. The contribution of this chapter is to shed light on the high

[1]Professor Alexander David developed this model

abnormal returns observed in a portfolio formed by unconstrained and low level of opinion divergence stocks. Intuitively, these stocks should be fairly priced as all the information (positive or negative) is incorporated into the prices in the absence of short sale constraints. In the empirical investigation, I find that a portfolio formed by stocks with low dispersion and low short interest ratio earns significantly higher future returns than a portfolio formed by otherwise similar stocks. I show that such portfolio contains stocks with low total and idiosyncratic risks, low growth, and low leverage. I also report that three and four factors models, as well as liquidity factors models, cannot account for these high abnormal returns.

Chapter 2

When is the Price of Dispersion Positive? with Alexander David

2.1 Introduction

Asset pricing implications of dispersion in investors' beliefs is among the most controversial issues in finance. Alternative theoretical and empirical frameworks have led to different signs on how dispersion affects stock returns.[1] The contribution of this paper is to show that the price of dispersion risk is time-varying in the cross-section, and potentially provides a resolution to the different views on the sign. Empirically, we find that in the cross-section of stock returns, aggregate dispersion is negatively priced in low dispersion months and positively priced in high dispersion months.[2] Our measure of aggregate dispersion is the value-weighted average of the standard deviation of analyst forecasts of the earning-per-share long-term growth rate at the firm level. This "bottom-up" measure has been used in

[1] On one hand, Varian (1985), Varian et al. (1989), Abel et al. (1989), Qu, Starks, and Yan (2003), Doukas, Kim, and Pantzalis (2004), Anderson, Ghysels, and Juergens (2005), David (2008), Anderson, Ghysels, and Juergens (2009) and Carlin, Longstaff, and Matoba (2014) find a positive relation. On the other hand, Miller (1977) theorizes that the divergence of investor's beliefs in the presence of short sale constraints leads to over-valuation and lower returns. In support of this hypothesis, Diether, Malloy, and Scherbina (2002), Chen, Hong, and Stein (2002) , Park (2005), Sadka and Scherbina (2007), and Yu (2011) find a negative relation between dispersion and excess returns.

[2] We define low (high) dispersion months as those when one-year lagged aggregate dispersion is lower (higher) than the average aggregate dispersion at minus (plus) one standard deviation.

several recent papers (e.g. Yu (2011) and Hong and Sraer (2016)) and incorporates the views of a vastly greater number of analysts than "top-down" measures, which are comprised of forecasts of the aggregate earnings growth rate.

We begin our empirical study by replicating the results of Yu (2011), who documents a negative relation between aggregate dispersion and market returns in the time series in the sample period from 1981 to 2005. Extending the sample to 2016, however, we find that the coefficient of aggregate dispersion is insignificant. Restricting the sample to 2006-2016, we see that the coefficient of aggregate dispersion is strongly positive. Looking at the time series of aggregate dispersion displayed in Figure 2.1, we see that the sample from 1981 to 2005 mainly had low dispersion months, while the sample from 2006 to 2016 mainly consisted of high dispersion months. This finding motivates our main idea that the sign of the price of dispersion risk depends on the level of dispersion.

To study the effects of aggregate dispersion on the cross-section of stock returns, we start by estimating the market and aggregate dispersion pre-ranking risk loadings, β and δ, using one-year rolling regressions at the monthly frequency of individual stock returns on excess market returns as well as one-month lagged aggregate dispersion. These estimated risk loadings allow us to analyze the price of dispersion risk using two different methods described next.

First, we form ten portfolios using, δ, the estimated aggregate dispersion loadings. Figure 2.2 highlights the role played by aggregate dispersion in asset's returns using the full sample, low, medium and high dispersion months. Using the full sample, we find a U-shaped relation between dispersion and portfolio returns. Limiting our sample to low (high) dispersion months, we see a clear negative (positive) relation between dispersion in investor's beliefs and returns. During low (high) dispersion months, a portfolio of stocks in the highest decile of dispersion loading underperforms (outperforms) a portfolio of stocks in the lowest decile of dispersion loading. In medium dispersion months, the relationship is unclear.

Second, we control for the CAPM by forming 100 β-δ portfolios. Every month, we sort stocks into 10 β-deciles using the pre-ranking β. Then, for every β-decile, we sort stocks based on the pre-ranking δ into 10-deciles. Using a Fama and MacBeth (1973) style two-stage regression on the 100 β-δ portfolios, we show that the price of dispersion risk is negative in low dispersion months (-6.067, t-statistic $= -4.52$) and positive in high dispersion months (24.92, t-statistic $= 4.67$). The price of dispersion risk is statistically insignificant using the full sample period or medium-dispersion months. We next show that our finding is robust to the choice of test portfolios, as it holds using a variety of portfolios obtained from the website of Ken French.

To better understand the changing sign of the price of dispersion risk, we construct a production economy N-asset general equilibrium model in the spirit of Merton's ICAPM, in which analysts of different types have heterogeneous beliefs and provide different forecasts of a macroeconomic factor (aggregate earnings growth). The consumer does not trust either analyst fully, and dynamically adjusts the weight given to each analyst, given the history of their past forecast performance. The beliefs of each analyst and the weight the consumer assigns to each analyst's forecast, become state variables in the ICAPM framework whose shifts the consumer hedges against. We derive an equilibrium cross-sectional pricing equation for our model. There are three terms in each asset's risk premium, which we discuss next.

The first term, is the risk premium for covarying with the market portfolio, as in the CAPM; however, in the model, the exposure to the market is measured by the relative cash-flow beta of each asset, rather than the return beta. The second term, measures the risk premium for bearing the risk in the aggregate macroeconomic factor as well as any undiversified idiosyncratic risk. The last term, is the risk premium with respect to a "flight-to-safety" factor. This factor depends on the variance of the market portfolio and has a negative sign. The negative sign on the term implies that assets that provide higher returns in periods when the variance is high, obtain a lower risk premium. The negative risk premium is consistent with the variance risk premium literature. The interesting aspect of this term is that it is time-varying and depends on the consumer's portfolio choices. As in Merton's ICAPM and Cox, Ingersoll, and Ross (1985), the representative consumer attempts to hedge against shifts in the state variables of the economy in addition to her diversification motive. The state variables in the economy are the beliefs of each analyst as well as a weight that the consumer places on the forecast of each analyst. The risk premia for shifts in these state variables, written as a function of the portfolio choices, collapses to the variance of the market portfolio. When analysts' dispersion becomes very high, consumers respond by allocating their investments to low cash flow beta assets, and this term declines. It is also interesting that the exposure to the flight-to-safety factor is again measured by the relative cash flow beta of each asset.

We estimate our model from 1971-2001 and out-of-sample beliefs of analysts are formulated until 2017. Using an unobserved regime shifting structure in the aggregate fundamental, which we take as aggregate S&P 500 operating earnings growth, we find two sets of parameters (one for each type of analyst), that maximizes the sum of the likelihoods of each agent type observing the fundamentals, and using the conditional expectations of each type of agent, we formulate the forecast of aggregate earnings growth, we formulate the 1-year ahead, aggregate earnings dispersion among the two types. The objective function also puts weight on matching the model dispersion to the dispersion of earnings growth from the Philadelphia Fed Survey of Professional Forecasters. The model provides a positive correlation between the dispersion in the analysts forecasts, and the price of dispersion risk and is higher in periods of high aggregate dispersion, as in the data.

A large literature in asset pricing has examined the risk-return trade-off. The Capital Asset Pricing Model of the Sharpe (1964), Lintner (1965) and Black (1972) states that the security excess return is proportional to the sensitivity of its return to the market return, denoted by CAPM beta. Jensen, Black, and Scholes (1972) point out that "high beta" assets earn lower returns on average. More recently, Frazzini and Pedersen (2014) document that a portfolio that holds low-beta assets and that shorts high-beta earns a positive average return. Hong and Sraer (2016) relax the CAPM homogeneous expectation assumption and show that when aggregate disagreement is low, expected return increases with beta due to risk-sharing confirming the CAPM prediction. However, when it is large, the expected return can decrease with beta through the "short-sale constraint" channel. Our paper complements this finding by having aggregate dispersion as an explicitly priced factor with a generally negative price of risk, which turns positive in periods of high aggregate dispersion.

On the theoretical front, our paper contributes to the growing literature on general equilibrium models with heterogeneous beliefs. starting with the seminal papers of Detemple and Murthy (1994) and Basak (2000). David (2008) studies the implications of heterogeneous beliefs for risk premium on the market index within this framework, while Dumas, Kurshev, and Uppal (2009) study the implications for "excess volatility" of the market index. Gallmeyer and Hollifield (2008) study the implications for asset prices in such a model with an added short-sales constraint, while Burashi, Trojani, and Vedolin (2014) extend the framework to multiple stocks in an exchange economy setting with multiple trees. Baker, Hollifield, and Osambela (2016) study investment in a single production technology where the representative agent has Epstein-Zin preferences. This paper is able to obtain a tractable equilibrium characterization by working with the Cox-Ingersoll-Ross (1985) framework with multiple firms, each having access to a linear production technology. In particular, the scale of each firm is endogenous, and we explicitly study the riskiness of the market portfolio with changing dispersion of beliefs. In addition, ours is the first model that makes a distinction between the beliefs of analysts, who we assume cannot trade in stocks, and the representative consumer, who does not directly follow firms' fundamental, but dynamically weights the forecasts of the different analysts in the economy.

The rest of this chapter is organized as follows. In Section 2, we describe the data used, define the aggregate dispersion measure and construct the β-δ portfolios. In Section 3, we present the results of the two-pass regressions. In Section 4, we provide a theoretical model that prices dispersion risk in the cross-section and show that its pricing implications are in line with our empirical findings. Section 5 concludes. The proofs of Propositions are in the working paper "When is the Price of Dispersion Risk Positive? "

2.2 Data and Variables

The data in this study are the intersection of the Institutional Brokers Estimate System (I/B/E/S) and the Center of Research in Securities Prices database (CRSP) between December 1981 and September 2016. From I/B/E/S database, we obtain the analyst forecasts data. From CRSP, we obtain the monthly returns and stock characteristics (volume, shares outstanding, price...). We include all stocks listed in New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and The Nasdaq Stock Market with share code 10 or 11 (common stocks). In order to ensure that the illiquid stocks are not considered in our analysis, we exclude penny stocks (price $<$ \$5) and micro-caps (stocks in the bottom two deciles of the monthly size distribution). A firm is kept in our sample if it has more then 12 consecutive monthly observations. We end up with a sample of 6428 firms.

2.2.1 Aggregate Dispersion

We start by displaying the primary variable of interest, the aggregate dispersion. Similar to Yu (2011), we measure the aggregate dispersion as the value-weighted average of the stock-level dispersion, where stock-level dispersion is the standard deviation of analyst forecasts of the earning-per-share long-term growth rate (EPS LTG). Figure 2.1 plots the time series of the aggregate dispersion measure as well as the low and high dispersion thresholds shown by the two horizontal lines. We define low (high) dispersion month (t) as the month where aggregate dispersion is lower (higher) than the average aggregate dispersion at $(t-1)$ minus (plus) one standard deviation. Out of 418 months, 87 months are considered high dispersion months, and only 55 months are considered low dispersion months. The remaining 276 months are considered medium dispersion months. Low dispersion months are concentrated before 2000. However, high dispersion months happen mostly after 2000. As can be seen in Figure 2.1, high levels of dispersion occur both during recession and growth periods. Table 2.1 presents the summary statistics of the aggregate dispersion measure. On average, during the full sample period, the aggregate dispersion equals 3.51. The average ranges from 2.8 in low dispersion months to 4.48 in high dispersion months. Our main empirical findings also hold using the β-weighted measure of aggregate dispersion used in Hong and Sraer (2016).

We begin our study by replicating and expanding Yu (2011) results. Yu documents that for the market portfolio, market dispersion is negatively related to market returns at different horizons. In Table 2.2, we regress the excess market return from month t to $t+h$ ($h = 1, 6, 12, 24, 36$ months) on the aggregate dispersion at month t. In Panel A, we use Yu (2011)'s sample period covering observations from December 1981 to December 2005. Figure 2.1 shows that this period is composed mainly of low aggregate dispersion months. Results are consistent with Yu's finding. The coefficient of aggregate dispersion is negative and significant for all return horizons, and the explanatory power of aggregate dispersion is more pronounced for higher horizons. In Panel B, we repeat the same exercise using our full sample period, including observations from December 1981 to September 2016, the coefficient of aggregate dispersion is negative but insignificant at all horizons. The effect of aggregate dispersion on market returns is less pronounced using the full sample compared to Yu (2011)'s sample. For example, at the two-year horizon, the coefficient of dispersion equals -9.27 (t-statistic = -1.17) using the full sample and equals -29.49 (t-statistic = -3.66) using data till December 2005. In Panel C, we only include the recent ten years of data to run our regressions. The last ten years of our monthly observations are mainly considered high dispersion months, as shown in Figure 2.1. Results show that aggregate dispersion is positively related to market returns. The coefficient of dispersion is significant only at the 3-year return horizon with a t-statistic of 2.74. These results motivate us to look more carefully at the cross-sectional regression of stocks return on aggregate dispersion and examine the relation of aggregate dispersion to assets returns at low, medium and high dispersion months.

In this part, we report the contemporaneous correlation between aggregate dispersion, stock market excess returns, and the standard pricing factors SMB, HML, and UMD in Table 2.3. We note that aggregate dispersion is weekly correlated with other variables using the full sample, which may imply that, if the aggregate dispersion affects stock returns, then the reason may be different from those for other factors. Using low dispersion months or medium dispersion months, aggregate dispersion is positively correlated with the market excess return and the size factor and negatively correlated with the value factor, and the momentum factor. Moreover, limiting our sample to the high dispersion months, aggregate dispersion is positively correlated with the market excess return, the size factor and the momentum factor and negatively correlated with the value factor. In the subsequent analysis, we show that aggregate dispersion remains significant after controlling for the standard pricing factors in various setting.

2.2.2 Pre-ranking Risk Loadings

To obtain time-varying risk loadings, we run rolling monthly time-series regressions of stock returns on excess market returns as well as one-month lagged aggregate dispersion.

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} \times R_{m,t} + \delta_{i,t} \times Agg\_disp_{t-1} + \epsilon_{i,t} \tag{2.1}$$

For each security, every month, we estimate the pre-ranking β and δ as the slope coefficients from time series regression of individual securities on excess market return as well as lagged aggregate dispersion using the previous 12 months of monthly observations. The estimated risk loadings $\beta_{i,t}$ and $\delta_{i,t}$ allow us to analyze the cross-sectional characteristics of these parameters in two different ways. First, we form portfolios based on δ, the dispersion risk exposure, and we look at the average returns for these classes of stocks. Second, we use cross-sectional two-stage regressions to examine the role of aggregate dispersion on stock returns.

2.2.3 Univariate Portfolio Sorts

We use the estimated aggregate dispersion exposure δ, obtained from regression 2.1, to test if aggregate dispersion is priced in the cross-section of stocks returns using four sample periods: full sample, low, medium and high dispersion months. To do so, we assign stocks into portfolios using the aggregate dispersion loadings. Each calendar month, we sort stocks into ten δ-deciles with the first decile having the lowest pre-ranking δ and the tenth decile having the highest pre-ranking δ. We calculate the monthly portfolio return, R_t^P, as the value-weighted average of the returns of all stocks in the P^{th} δ-sorted portfolio. Figure 2.2 highlights the role played by aggregate dispersion in asset's returns. Panel A plots the aggregate portfolio returns using the full sample. We notice a U-shaped relation between dispersion and returns. Panel B uses only the low dispersion months; we clearly detect the negative relation between dispersion in investor's beliefs and returns. Panel C plots the sorting results using medium dispersion months; the graph does not show a clear relationship between dispersion and returns. Panel D reports the sorting results for high dispersion months; we now observe a strong positive relation between dispersion and portfolio returns.

2.3 The Price of Dispersion Risk in the Cross-Section

2.3.1 Two-stage Regression

In this section, we turn our attention to analyze whether the aggregate dispersion is a priced risk factor using our value-weighted β-δ portfolios. To construct the β-δ portfolios, we use the estimated parameters, β and δ, obtained from equation (2.1). Every month, we sort stock into 10 β-deciles using the pre-ranking β. For every β-decile, we sort stocks based on the pre-ranking δ. We obtain 100 portfolios formed monthly. We calculate the value-weighted monthly returns R_t^P on these 100 portfolios. We report the summary statistics in Table 2.4 for monthly β-δ portfolio return and pre-ranking risk loadings. The numbers reported represent time-series averages of the monthly cross-sectional mean, standard deviation and the 10^{th} to 90^{th} percentile.

We use four regression models to estimate portfolio post-ranking β and post-ranking δ. As suggested by Fama and MacBeth (1973), Jensen et al. (1972) and Cochrane (2009), we form portfolio to estimate the post-ranking risk loadings. Model one includes the market excess returns. Model two adds the one-month lagged aggregate dispersion measure. Model three includes the Fama and French (1993) factors and the momentum factor (Jegadeesh and Titman (1993)). And Model four, displayed in equation 2.2, includes all the variables listed above. We obtain monthly returns on the factors (R_t^m, SMB, HML, and UMD) from Ken French's data web site. Every calendar month, post-ranking risk loadings are estimated using the previous one-year of monthly returns.

$$\begin{aligned} R_t^P = {} & \alpha_{P,t} + \beta_{P,t}^{MKT} \times R_t^m + \delta_{P,t} \times Agg\_disp_{t-1} \\ & + \beta_{P,t}^{SMB} \times SMB_t + \beta_{P,t}^{HML} \times HML_t + \beta_{P,t}^{UMD} \times UMD_t + \epsilon_{P,t}, \quad (2.2) \end{aligned}$$

where, $P = 1, ..., 100$, R_t^P is the value-weighted monthly return of the P^{th} $\beta - \delta$-sorted portfolio at t, R_t^m is the market excess return at t, Agg_disp_{t-1} is the value-weighted aggregate dispersion at month *(t-1)*, SMB_t is the average return on the three small portfolios minus the average return on the three big portfolios, HML_t is the average return on the two value portfolios minus the average return on the two growth portfolios and UMD_t is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. We now define the portfolio post ranking β_P^{MKT} as the time series average of $\beta_{P,t}^{MKT}$ and the portfolio post ranking δ_P as the time series average of $\delta_{P,t}$. Second, as in Fama and MacBeth (1973), each calendar month, we estimate the four cross-sectional regressions over our 100 β-δ portfolios using the specification

$$R_t^P = \kappa_t + \pi_t \times \beta_P^{MKT} + \omega_t \times \delta_P + \phi_t^{SMB} \times \beta_P^{SMB} + \phi_t^{HML} \times \beta_P^{HML} + \phi_t^{UMD} \times \beta_P^{UMD} + \epsilon_{t,P}, \quad (2.3)$$

where $P = 1, ..., 100$, β_P^{MKT} , δ_P, β_P^{SMB}, β_P^{HML} , β_P^{UMD} are the time series averages of the post-ranking portfolio loadings of the P^{th} $\beta - \delta$-sorted portfolio estimated using regression 2.2.

Table 2.5 reports the average month-by-month regression coefficients estimates as well as the t statistics, which are adjusted as proposed by Shanken (1992). We also report the average month-by-month coefficients of determination R^2. The dependent variable in columns 1 - 4, R_t^P, is the return of the P^{th} $\beta - \delta$-sorted portfolio at t. The independent variable of interest is the time series average of dispersion risk loading δ_P. The first column, shows the simple CAPM results. In the second column, we include the market loading, β_P^{MKT} as well as the dispersion loading, δ_P, as independent variables in our regression. The price of dispersion risk is positive, 0.989% but insignificant with a t-statistic of 0.92. R^2 equals to 51% higher then the CAPM R^2 of 24%. In the fourth column, we extend our analysis to control for size, value, and momentum effects. The price of dispersion risk is still positive (0.851%) and insignificant with a t-statistic of 0.76.

Evidence from both Fama MacBeth regressions and portfolio sorts suggests that the aggregate dispersion effect on stock returns varies across different sample periods. To test this hypothesis, we first retrieve a time series of the price of dispersion, ω_t. Figure 2.3 plots the time series of the price of dispersion risk estimated by the following two-factor regression:

$$R_t^P = \kappa_t + \pi_t \times \beta_P^{MKT} + \omega_t \times \delta_P + \epsilon_{t,P},$$

where $P = 1, ..., 100$. We also plot in shaded area low and high dispersion months. We clearly notice that low dispersion months, shown in light grey, display negative values of price of dispersion risk. High dispersion months, shown in dark grey, display positive values of price of dispersion risk. These results strongly confirm that aggregate dispersion displays a time-varying risk premium.

In the next step, we run a two-stage regression to formally analyze the effect of aggregate dispersion in three different sub-samples: low, medium, and high dispersion months. Table 2.6 column 2 reports the model two second-stage regression results, where the two independent variables are the market and dispersion loadings. Results suggest that, in periods of low beliefs dispersion (panel A), the coefficient of the exposure to aggregate dispersion is negative -6.07% and significant (t-statistic $= -4.52$) and in periods of high beliefs dispersion (Panel C), the coefficient of δ_P is positive 24.92% and significant (t-statistic $= 4.66$). However, in period of medium aggregate dispersion (Panel B), the price of dispersion risk is insignificant (t-statistic $= -0.20$) and very low (-0.24%). R^2s are around 50% in the three subsamples, higher than the CAPM R^2s equal to 22%, 24% and 23% in low, medium and high dispersion months respectively. These values of R^2 suggest that aggregate dispersion is an important state variable. Controlling for size, value, and momentum factors generates equally good results. Column 4 shows that the aggregate dispersion risk loading is negatively related to portfolio returns in low dispersion months (Panel A), the coefficient of δ_P is equal to -6.32% with a t-statistic of -4.48 and it is positively related to portfolio returns in high dispersion months (Panel C) with a coefficient of 24.84% and a t-statistic of 4.74. Again, medium aggregate dispersion months (Panel C) display insignificant and low price of dispersion risk. The R^2s are around 54% using the three different sub-samples, again higher than the four factors model R^2s presented in column 3.

Overall, the results of Table 2.6 strongly suggest that the aggregate dispersion effect on portfolio returns is time-varying. In particular, it is positive in high dispersion months and negative in low dispersion months. It is worth noting that the magnitude of the price of dispersion risk is more pronounced in high dispersion months (24.92% in column 2 and

24.84% in column 4) compared to the low dispersion months (−6.067% in column 2 and −6.325% in column 4) and almost equals to zero (−0.236% in column 2 and −0.414% in column 4) in medium dispersion months.

2.3.2 Additional Test Portfolios

In this section, we study whether the aggregate dispersion is a priced risk factor using test portfolios. In order to alleviate the critique of Lewellen, Nagel, and Shanken (2010), ten sets of tests portfolios are used: 25 Value Size Portfolios, 25 Net Share Issues Size Portfolios, 10 Size Portfolios, 10 Value Portfolios, 25 Size Investment Portfolios, 100 Size Operating Prof Portfolios, 30 Industry Portfolios, 10 E/P Portfolios, 10 Net Share Issues Portfolios, 25 Book-to-Market and Operating Profitability Portfolios. We obtain value-weighted monthly returns on these portfolios from Ken French's data web site.

First, every month, we estimate the risk loadings from a rolling time series regression of portfolio returns on excess market returns and one-month lagged aggregate dispersion using the previous 12 months. Similar to our analysis using the 100 β-δ portfolios, we also include Fama and French (1993) factors and the momentum factor (Jegadeesh and Titman (1993)) to control for size, value and momentum effects.

Second, we estimate the prices of risk by regressing the value-weighted portfolio return on the first-pass risk loadings. Tables 2.8 and 2.9 summarize the second pass regressions using the overall sample period for the 10 test portfolios listed above. Results show that the sign of the price of dispersion risk is undetermined. Table 2.8, reports the results of the two-factor model with market excess return and aggregate dispersion being the two factors considered. The coefficient of aggregate dispersion risk loading is positive for six out of our ten portfolios. Only one of these six portfolios (25 Book-to-Market and Operating Profitability Portfolios) displays a significant price of dispersion risk. Table 2.9 includes the market, dispersion, size, value, and momentum risk loadings in the regression. Only four portfolios out of ten display positive price of dispersion risk with t-statistics below conventional significance levels.

At this stage of our analysis, we investigate the time-varying characteristics of the aggregate dispersion using the ten test assets listed above. To do that, we repeat the steps of the two-stage regression mentioned above using the low, medium, and high dispersion months. Tables 2.10 and 2.11 report the second-stage regressions. The price of dispersion is negative in low dispersion months, and positive is high dispersion months for eight out of the ten test assets. These results hold using the two-factor model in Table 2.10 and the full specification model in Table 2.11. However, the t statistics are low. Also, the magnitude of the price of risk is well pronounced in high dispersion months compared to the low dispersion months. In particular, the two-factor regression results using the 10 size portfolios show that the price of dispersion risk equals 41.97% (t statistic = 1.58), compared to -6.57% (t statistic = 0.86) in low dispersion months.

These empirical findings emphasize that the effect of aggregate dispersion on the portfolio returns varies with respect to the level of disagreement on the market. Low dispersion periods are characterized with negative dispersion price, and high dispersion periods are associated with positive dispersion price of risk.

2.4 The Model

In this section, we provide a general equilibrium model that sheds light on why the price of dispersion risk can change sign over time depending on the level of aggregate dispersion. The model is based on the framework of Cox et al. (1985) with two important specification choices. First, the state variables that we choose are the beliefs of each analyst type in the economy, and second, since we are modeling investment by a representative consumer, we restrict all portfolio choices to be non-negative.

2.4.1 The Macroeconomic Factor

A macroeconomic factor follows the process:

$$\frac{dY_t}{Y_t} = \nu_t dt + \sigma_Y d\tilde{W}_{Yt}. \tag{2.4}$$

The drift ν follows a 2-state Markov chain and it shifts between the states $\{\nu_1, \nu_2\}$ with generator matrix Λ.[3]

There are two types of analysts indexed by $m = 1, 2$. Each type m assumes that the process for ν has the correct specification, but differs in the estimates of the states as well as the generator. Let $\nu^{(m)}$ denote the estimated drift vector estimated by agent of type m, and let $\Lambda^{(m)}$ be their estimated generator matrix. Neither type of agent can observe the realizations of ν, although each does observe the entire history of Y. Based on their assumed models, analysts of type m form the posterior probability (see David (1997)) $\pi_{1t}^{(m)} = \text{prob}(\nu_t = \nu_1^{(m)} | \mathcal{F}_t^{(m)})$ of ν being in state 1 at time t. I denote conditional means with bars, for example, $\overline{\nu}_t^{(m)} = \sum_{i=1}^{2} \pi_{it}^{(m)} \nu_i^{(m)}$. Given an initial belief $0 \leq \pi_{10}^{(m)} \leq 1$, the probabilities $\pi_{1t}^{(m)}$ follow the stochastic differential equations

$$d\pi_{1t}^{(m)} = \mu_{1t}^{(m)} dt + \sigma_{1t}^{(m)} d\tilde{W}_{Yt}^{(m)}, \tag{2.5}$$

where

$$\mu_{1t}^{(m)} = (\Lambda_{12}^{(m)} + \Lambda_{21}^{(m)})[\pi_1^{*(m)} - \pi_{1t}^{(m)}], \tag{2.6}$$

$$\sigma_{1t}^{(m)} = \pi_{1t}^{(m)}(1 - \pi_{1t}^{(m)}) \frac{(\nu_1^{(m)} - \nu_2^{(m)})}{\sigma_Y}, \tag{2.7}$$

$$d\tilde{W}_{Yt}^{(m)} = \frac{1}{\sigma_Y} \left(\frac{dY_t}{Y_t} - E_t^{(m)}[\frac{dY_t}{Y_t}] \right) = \frac{(\nu_t - \overline{\nu}^{(m)})}{\sigma_Y} dt + d\tilde{W}_{Yt}. \tag{2.8}$$

[3]Over the infinitesimal time interval of length dt, $\Lambda_{ij} dt = \text{prob}\,(\nu_{t+dt} = \nu_j | \nu_t = \nu_i)$, for $i \neq j$, and $\Lambda_{ii} = -\Lambda_{ij}$. The transition matrix over any finite interval of time, s, is $\exp(\Lambda s)$.

In particular, $\pi_{1t}^{(m)}$ mean reverts to its unconditional mean, $\pi_1^{*(m)} = \Lambda_{21}^{(m)}/(\Lambda_{12}^{(m)}+\Lambda_{21}^{(m)})$, with a speed proportional to $(\Lambda_{12}^{(m)}+\Lambda_{21}^{(m)})$, and the volatility of an agent of type m's updating process is the product of his uncertainty, $\pi_{1t}^{(m)}(1-\pi_{1t}^{(m)})$, and the signal-to-noise ratio, $\frac{(\nu_1^{(m)}-\nu_2^{(m)})}{\sigma_Y}$.

The two types of agents perceive the history of fundamentals differently. The process $\{\tilde{W}_{Yt}^{(m)}\}$ is the "innovations" process of analysts of type m, and is the shock process to the macroeconomic factor as perceived by agents of type m. According to analyst m, the macroeconomic factor dynamics are:

$$\frac{dY_t}{Y_t} = \bar{\nu}^{(m)}dt + \sigma_Y d\tilde{W}_{Yt}^{(m)}. \tag{2.9}$$

Taking the difference between the innovations of the two analysts we have

$$d\tilde{W}_{Yt}^{(2)} = d\tilde{W}_{Yt}^{(1)} + \sigma_{\eta t}dt, \tag{2.10}$$

where $\sigma_{\eta t} = \frac{(\bar{\nu_t}^{(1)}-\bar{\nu_t}^{(2)})}{\sigma_Y}$. Let $\mathcal{P}_t^{(m)}$ be analyst m's probability measure over the path of Y_s, $s \in [0,t]$. Again appealing to the results in David (2008) (see Corollary 1), the Radon-Nikodym derivative of $\mathcal{P}_t^{(2)}$ with respect to $\mathcal{P}_t^{(1)}$ is given by the process η_t, which follows;

$$\frac{d\eta_t}{\eta_t} = \sigma_{\eta t} d\tilde{W}_{Yt}^{(1)}, \tag{2.11}$$

which is a martingale with respect to $\mathcal{P}_t^{(1)}$. By relating the two innovations processes, we can write the beliefs of analyst 2 from the eyes of analyst 1 as

$$d\pi_{1t}^{(2)} = (\mu_{1t}^{(2)} + \sigma_{1t}^{(2)}\sigma_{\eta_t})dt + \sigma_{1t}^{(2)} d\tilde{W}_{Yt}^{(1)}, \tag{2.12}$$

and consequently solve the equilibrium of the model under analyst 1's probability measure.[4]

[4] Alternatively, we could also solve it under analyst 2's probability measure, or even the objective probability measure.

2.4.2 Speculation Among the Analysts

The analysts are able to speculate with each other on the realized value of the fundamental process Y.[5] Following Basak (2000), equilibrium among the analysts can be solved as the solution to the social planner's problem at each time t with weights $\lambda_{2t}/\lambda_{1t} = k\,\eta_t$, where η_t is the process in (2.11), and k is a constant that depends on the ratio of the initial wealths of the analysts at date 0. As discussed in David (2008), in equilibrium, $\eta_t = \xi_t^{(1)}/\xi_t^{(2)}$, which is the ratio of the analysts' state price densities (SPDs). Since the SPD is the state price per unit probability of the state at date t, and the analysts agree on the state prices, η_t is the ratio of the probability of the state arising from the model of analyst 2, divided by the probability of the state arising from the model of analyst 1. Clearly, η_t belongs to the interval $[0, \infty]$. To obtain a bounded state variable set, we define

$$\varrho_t = \frac{1}{1+\eta_t}, \tag{2.13}$$

which is in $[0, 1]$, and in the competitive equilibrium, is the posterior probability that the macro fundamental Y_t at date t arises from the model of analyst 1.[6] Similarly $1 - \varrho_t$ is the posterior probability that the data is generated by the model of analyst 2. By Ito's Lemma, $\{\varrho_t\}$ satisfies the process:

$$d\varrho_t = \varrho_t\,(1-\varrho_t)^2\,\sigma_{\eta t}\,dt - \varrho_t\,(1-\varrho_t)\,\sigma_{\eta t} dW_t^{(1)}. \tag{2.14}$$

2.4.3 Firms in the Economy

We model firms in a production economy with stochastically linear technologies as in Cox et al. (1985). We assume that there are N production technologies, which we shall simply

[5] This could be done by derivative securities whose value mirrors that of Y.

[6] Using Bayes' law over model likelihoods with uninformative priors, the posterior probability that the data at t arises from the model of agent 1 equals $\frac{0.5\,\text{Prob}(Y_t|\text{Analyst 1's model})}{0.5\,\text{Prob}(Y_t|\text{Analyst 1's model})+0.5\,\text{Prob}(Y_t|\text{Analyst 2's model})} = \varrho_t$.

refer to as assets. The transformation of an investment of an amount X_i of the single good in the economy in the ith asset is given by the

$$\frac{dX_{it}}{X_{it}} = b_i \frac{dY_t}{Y_t} + \sigma_i d\tilde{W}_i. \tag{2.15}$$

Therefore the return on each technology is driven by the macroeconomic factor and an an idiosyncratic firm specific shock. The coefficient b_i is the "cash-flow beta" of the ith technology. We order firms in the economy with the ratio b_i/σ_i, so that

$$0 < \frac{b_1}{\sigma_1} < \frac{b_2}{\sigma_2} \cdots < \frac{b_N}{\sigma_N}. \tag{2.16}$$

Investment in the assets is made through competitive value maximizing firms. With free entry of firms and stochastic constant returns to scale, there is no incentive for firms to enter or leave industry i if and only if the returns on the shares of each firm are identical to the technologically determined physical returns on that asset. The equilibrium scale of each firm is determined by the supply of investment to that firm.

2.4.4 Consumers in the Economy

In contrast to models in the heterogeneous beliefs literature (for example Basak (2000) or David (2008) and the references in the introduction), we make a distinction between analysts and consumers. Analysts do not trade in stocks, but on derivatives on the macroeconomic factor. The representative consumer in the economy has the standard CRRA utility function

$$U(c) = E^{(m)}[\int_0^\infty \exp(-\rho s) \cdot u(c_s) ds], \tag{2.17}$$

with time discount factor ρ and felicity $u(c_t) = c_t^\gamma/\gamma$. The felicity function $u(.)$ has a constant coefficient of relative risk aversion $1-\gamma$, and satisfies the Inada conditions $\lim_{c\to 0} u'(c) = \infty$ and $\lim_{c\to\infty} u'(c) = 0$.

We assume that the representative consumer does not fully trust any particular analyst in the economy, but behaves as a Bayes' Model Averager (BMA). However, she assesses analyst's relative performance and in particular uses the assessed probabilities that the data at any given date is generated by model of analyst m and given the analysts' equilibrium in Section 2.4.2, assign weights of ϱ_t and $1-\varrho_t$, to the beliefs of analysts 1 and 2, respectively. Given the asset return distributions in (2.15), the consumer's expected return for asset i is $\alpha_i = b_i(\varrho_t \bar{\nu}^{(1)} + (1-\varrho_t)\bar{\nu}^{(2)})$. Let $w_i \geq 0$ be the proportion of the consumer's wealth invested in asset i for $i = 1, \cdots, N$, and w_0 be the proportion invested in the instantaneous riskless bond in the economy, which offers a rate of return r_t, and is in zero net supply. We will first solve the social planner's problem for the representative agent economy, which does not include investment in the riskless asset, and hence the portfolio weights satisfy $\sum_{i=1}^N w_i = 1$. Later, we will find the rate at which a choice of $w_0 = 0$ is optimal. Then, the consumer's wealth dynamics can be written as

$$dW_t = -C_t dt + W_t \left[\sum_{i=1}^{N} w_i \alpha_i dt + w_i b_i \sigma_Y d\tilde{W}_{Yt} + w_i \sigma_i d\tilde{W}_i \right], \tag{2.18}$$

where C_t is the rate of consumption.

Given the beliefs and the analysts' model probabilities, we can formulate the equilibrium in the production economy as in Cox et al. (1985).[7] We start with the social planner's problem in this economy.

Proposition 1. *The value function of the representative consumer in the economy that maximizes utility takes the form:*

$$J(W_t, \pi_{1t}^{(1)}, \pi_{1t}^{(2)}, \varrho_t, t) = \exp(-\rho t) \frac{W_t^\gamma}{\gamma} I(\pi_{1t}^{(1)}, \pi_{1t}^{(2)}, \varrho_t), \tag{2.19}$$

[7] David (1997) extends the CIR model to the case with unobserved drifts of the production processes and learning.

in which the function $I(\pi_{1t}^{(1)}, \pi_{1t}^{(2)}, \varrho_t)$ *satisfies the PDE:*

$$
\begin{aligned}
0 = \max_{w_i, s.t. w_i \geq 0, \sum_{i=1}^N w_i = 1} \Bigg[& \left(\frac{1}{\gamma} - 1\right) I^{\frac{\gamma}{\gamma-1}} - \frac{\rho}{\gamma} I \\
& + I \left(\sum_{i=1}^N w_i b_i (\varrho\, \bar{\nu}^{(1)} + (1-\varrho)\, \bar{\nu}^{(2)}) + \frac{1}{2}(\gamma - 1) \sum_{i=1}^N w_i^2 (b_i^2 \sigma_Y^2 + \sigma_i^2) \right) \\
& + I_{\pi_1^{(1)}} \left(\frac{\mu_1^{(1)}}{\gamma} + (\sum_{i=1}^N w_i b_i) \sigma_1^{(1)} \sigma_Y \right) + I_{\pi_1^{(2)}} \left(\frac{\mu_1^{(2)} + \sigma_2^{(2)} \sigma_\eta}{\gamma} + (\sum_{i=1}^N w_i b_i) \sigma_1^{(2)} \sigma_Y \right) \\
& + I_\varrho \left(\frac{\varrho(1-\varrho)^2 \sigma_\eta}{\gamma} - (\sum_{i=1}^N w_i b_i) \varrho (1-\varrho) \sigma_\eta \right) \\
& \frac{1}{2} I_{\pi_1^{(1)} \pi_1^{(1)}} (\sigma_1^{(1)})^2 + \frac{1}{2} I_{\pi_1^{(2)} \pi_1^{(2)}} (\sigma_1^{(2)})^2 + \frac{1}{2} I_{\varrho\varrho} \varrho^2 (1-\varrho)^2 \sigma_\eta^2 \\
& - I_{\pi^{(1)}\varrho} \sigma_1^{(1)} \varrho (1-\varrho) \sigma_\eta - I_{\pi^{(2)}\varrho} \sigma_1^{(2)} \varrho (1-\varrho) \sigma_\eta + I_{\pi^{(1)}\pi^{(2)}} \sigma_1^{(1)} \sigma_1^{(2)} \Bigg]. \quad (2.20)
\end{aligned}
$$

The Kuhn-Tucker first-order conditions for the portfolio choices of the consumer are:

$$
\begin{aligned}
& b_i(\varrho\, \bar{\nu}^{(1)} + (1-\varrho)\, \bar{\nu}^{(2)}) + (\gamma - 1) w_i (b_i^2 \sigma_Y^2 + \sigma_i^2) + \frac{I_{\pi_1^{(1)}}}{I} b_i \sigma_1^{(1)} \sigma_Y + \frac{I_{\pi_1^{(2)}}}{I} b_i \sigma_1^{(2)} \sigma_Y \\
& \quad - \frac{I_\varrho}{I} b_i \varrho (1-\varrho) \sigma_\eta \sigma_Y + \kappa_i - \frac{\lambda^{(1)}}{I} \leq 0 \qquad \text{for} \quad i = 1, \cdots, N \quad (2.21)
\end{aligned}
$$

$$
\begin{aligned}
& w_i \Bigg[b_i(\varrho\, \bar{\nu}^{(1)} + (1-\varrho)\, \bar{\nu}^{(2)}) + (\gamma - 1) w_i (b_i^2 \sigma_Y^2 + \sigma_i^2) + \frac{I_{\pi_1^{(1)}}}{I} b_i \sigma_1^{(1)} \sigma_Y + \frac{I_{\pi_1^{(2)}}}{I} b_i \sigma_1^{(2)} \sigma_Y \\
& \quad - \frac{I_\varrho}{I} b_i \varrho (1-\varrho) \sigma_\eta \sigma_Y + \kappa_i - \frac{\lambda^{(1)}}{I} \Bigg] = 0 \qquad \text{for} \quad i = 1, \cdots, N \quad (2.22)
\end{aligned}
$$

$$
\begin{aligned}
\sum_{i=1}^N w_i &= 1 && (2.23) \\
w_i &\geq 0; i = 1, \cdots, N && (2.24) \\
w_i \kappa_i &= 0; i = 1, \cdots, N, && (2.25)
\end{aligned}
$$

where $\lambda^{(1)}$ *is the multiplier associated with the constraint* $\sum_{i=1}^{N} w_i = 1$*, and* κ_i *are the multipliers associated with the constraints* $w_i \geq 0$ *for* $i = 1, \cdots, N$*.*

The proof can be found in the working paper "When is the Price of Dispersion Risk Positive?"with Alexander David.

We solve the PDE in (2.20) with Chebyshev polynomials using projection methods. A similar PDE has been solved in David (2008), and we follow the steps there in implementing this method. One difference though is that the PDE in David (2008) did not have the portfolio choices, which are needed here. We follow a recursive procedure to determine the portfolio choices and the solution to the PDE. Given the *nth* iteration of the solution, I^n, we solve the portfolio choices w^{n+1} using (2.21) – (2.25) using a standard equation solver at each point on the Chebshev grid. We then, use these portfolio choices in finding the projections to the polynomials, and hence find I^{n+1}. Using standard contraction mapping arguments, the recursive procedure converges.

2.4.5 The Cross Section of Equilibrium Risk Premia in the Economy

We now consider the cross section of equilibrium risk premia for the different stocks in the economy.

Proposition 2. *In equilibrium, the risk premium for stock* i *for any stock with* $w_i > 0$ *satisfies:*

$$\alpha_i - r = \frac{b_i}{b_m}(\alpha_m - r) + (1 - \gamma)(b_i^2 \sigma_Y^2 + \sigma_i^2) - \frac{b_i}{b_m}(1 - \gamma)\sum_{i=1}^{N} w_i^2 (b_i^2 \sigma_Y^2 + \sigma_i^2), \quad (2.26)$$

in which $b_m = \sum_{i=1}^{N} w_i\, b_i$ *is the cash flow beta of the market portfolio, and* $\alpha_m = \sum_{i=1}^{N} w_i\, \alpha_i$ *is the expected return on the market portfolio. The riskless rate in the economy satisfies:*

$$r = \left(\sum_{i=1}^{N} w_i b_i\right) \left[(\varrho\, \bar{\nu}^{(1)} + (1-\varrho)\, \bar{\nu}^{(2)}) + \frac{I_{\pi_1^{(1)}}}{I}\, \sigma_1^{(1)} \sigma_Y + \frac{I_{\pi_1^{(2)}}}{I}\, \sigma_1^{(2)} \sigma_Y \;-\; \frac{I_\varrho}{I} \varrho (1-\varrho) \sigma_\eta \sigma_Y \right] + \; (\gamma - 1) \sum_{i=1}^{N} w_i^2\, (b_i^2 \sigma_Y + \sigma_i^2) \quad (2.27)$$

The proof can be found in the working paper "When is the Price of Dispersion Risk Positive?" with Alexander David.

We provide some comments on the equilibrium cross-sectional pricing equation in (2.26). There are three terms in each asset's risk premium. The first term, is the risk premium for covarying with the market portfolio, as in the CAPM; however, in the model, the exposure to the market is measured by the relative cash-flow beta of each asset, rather than the return beta. The second term, measures the risk premium for bearing the risk in the aggregate macroeconomic factor as well as any undiversified idiosyncratic risk. The last term, is the risk premium with respect to a "flight-to-safety" factor. As can be seen, this factor depends on the variance of the market portfolio. The negative sign on the term implies that assets that provide higher returns in periods when the variance is high, obtain a lower risk premium. The negative risk premium is consistent with the variance risk premium literature. The interesting aspect of this term is that it is time-varying and depends on the consumer's portfolio choices. As in Merton's ICAPM and Cox et al. (1985), the representative consumer attempts to hedge against shifts in the state variables of the economy in addition to her diversification motive. The state variables in the economy are the beliefs of each analyst $\pi_t^{(m)}$ about the state of the macro fundamental, as well, as the variable ϱ_t, which is the probability at any time that the fundamentals are generated by the model of agent 1. The risk premia for shifts in these state variables, written as a function of the portfolio choices, collapses to the third term, which is the variance of the market portfolio. As we will see, when analysts' dispersion becomes very high, consumers respond by allocating their investments to low cash flow beta assets, and this term declines. It is also interesting that the exposure to the flight-to-safety factor is again measured by the relative cash flow beta of each asset.

As noted above, the most interesting aspect of our model is that the loading on aggregate dispersion depends on the portfolio choices, which are the market weights in equilibrium. To illustrate why our model implies that the price of dispersion risk depends on the level of dispersion, consider the following situations. Suppose there are only two assets in the economy, with $b_1 = 0.1$ and $b_2 = 2$. Suppose uncertainty about the growth rate of Y is very high, so that $w_1 = 0.9$, and $w_2 = 0.1$ Now the term $\sum_i w_i^2 b_i^2$, which is in the last term is just 0.0481. Alternatively, when uncertainty is low suppose the weights reverse, $w_1 = 0.1$ and $w_2 = 0.9$, this term equals 3.24. Since the last term enters with a negative sign in the risk premium (the consumer likes an asset that gives a positive return when the variance is high), the model implies that the risk premium will be higher in periods of higher aggregate dispersion. We will formalize this intuition in the calibration section below.

To address the empirical results in our paper, we proceed to two-stage regressions on the market return and the aggregate dispersion in the economy.

2.4.6 Belief Calibration and Model Two-Stage Regressions

We calibrate the model as in David (2008). A brief description of the calibration method is as follows. Using the unobserved regime shifting structure in the aggregate fundamental, which we take as aggregate S&P 500 operating earnings growth, we find two sets of parameters (one for each type of analyst), that maximizes the sum of the likelihoods of each agent type observing the fundamentals, and using the conditional expectations of each type of agent, we formulate the forecast of aggregate earnings growth, we formulate the 1-year ahead, aggregate earnings dispersion among the two types. The objective function also puts weight on matching the model dispersion to the dispersion of earnings growth from the Philadelphia Fed Survey of Professional Forecasters. The calibrated parameters are shown in Table 2.7. In Figure 2.4 we see the beliefs of each analyst type for the sample from 1971 to 2001, as well as their estimates of earnings growth for the period from 1971 to 2001. As seen, the analyst of type 2 is more volatile. In addition, their expectations' differences are countercyclical, and the dispersion in their estimates is low in upturns and significantly higher in downturns.

Using the calibrated parameters, we simulate the model. The steps taken are as follows. We first extend the beliefs out-of-sample from 2002-2017 using the calibrated parameters and realized earnings growth. Using these beliefs, we similarly extended $\{\varrho_t\}$ series, which is the conditional probability that the agents assign to the model of analyst 2. For the cross-sectional specification, we use 10 assets, with cash flow betas that are $b_1 = 0.1$, $b_2 = 0.3$, ... $b_{10} = 0.2$. We use the same idiosyncratic volatility of 0.3 for each asset. Finally, for the consumer's preference, we use a time discount, ρ, of 2 percent, and a γ of 0.5. This low level of risk aversion (similar to that in David (2008), provides a low riskless rate. In addition, this choice implies an elasticity of intertemporal substitution, which is larger than 1, which has been documented in various studies. Using the beliefs and ϱ_t, we calculate the market portfolio weights as shown in Proposition 1. Then similar to the data, using rolling one-year lagged stock returns, we first run first-pass regressions of each asset's return on the market return and earnings dispersion. In the second-pass regression, at each date, we run the one-year lagged stock returns for each of the ten assets on the average of beta and delta over the full sample.

The results of the out-of-sample calibration exercise are seen in Figures 2.6 to 2.8. The top panel Figure 2.6 shows the historical operating earnings growth of S&P 500 firms over the full sample from 1971 - 2017, while the bottom panel shows the conditional probability that the model of Analyst 2 generated the data at each time t, which is ϱ_t. As can be seen, the pattern of analysts' expectations post-2001 is very similar to that prior to 2001 (our calibration sample). In particular, the expectations of Analyst 1 are more volatile, overshooting those of Analyst 2 in each direction, and the gap between them is significantly wider in downturns. Figure 2.7 shows the expected growth over the next one year of each analyst type (top-left), and the dispersion of their forecasts (top-right). The bottom-left panel shows the time-series of the market's cash flow beta, which is obtained by using the beliefs of each type, ϱ_t, and the optimal portfolio choices in Proposition 1. Finally, the bottom-right panel shows well the "flight-to-safety" pattern in the portfolio choices. Indeed, the cash flow beta of the market portfolio is nearly perfectly negatively correlated with the dispersion in analysts' forecasts. That is, when the consumer sees a large dispersion, she chooses lower cash-flow assets in her portfolio.

The time-series of the model's prices of risk from the second-pass are shown in Figure 2.8. While not readily evident, the two prices of risk have a negative correlation of -0.26, and each fluctuates in sign. We focus or comments on the price of dispersion risk. As seen, the model's price or risk changes sign over time. Its maximum value is as high as 0.27, and as low as -0.28. The correlation between the dispersion price of risk and dispersion of analysts' forecasts is 0.2, so that in the period of high dispersion, the price of dispersion risk tends to be higher, as in the data. Restricting our sample to periods when the dispersion is higher than its mean plus one standard deviation, the average price of dispersion risk is 0.06, while for the remaining sample, it is -0.03. This is consistent with our main empirical fact. The intuition for the positive correlation between dispersion and the price of dispersion risk is in our comments below Proposition 2. In periods of higher dispersion, the consumer invests in lower beta assets (as seen in Figure 2.7) and hence the loading on equilibrium loading on dispersion increases.

2.4.7 The Flight-to-Safety Effect in the Data

As discussed above, the change in the price of risk is related to the flight-to-safety behavior of consumers in the economy. In periods of high dispersion, consumers choose assets with lower cash flow betas. Here we verify that such a flight-to-safety occurs in the data. To do so, we first calculate a cash flow beta, b_i for each firm in the economy, which is estimated using 5-year rolling windows of firm-level earnings growth on aggregate earnings growth. The weight, w_i is the market capitalization weight of each stock in the CRSP database. In Figure

2.9, we show the time series of aggregate dispersion, as well as the term $\sum_i b_i^2 \cdot w_i^2$, which is in the third term of the model risk premium in equation (2.26). It is interesting to see that during recessions and financial crises, this term declines. Such periods also happen to be in periods of high dispersion. Indeed, the two series have a correlation of -0.39; that is, there a portfolio reallocation towards lower cash flow beta assets in periods of higher dispersion, consistent with our model.

2.5 Conclusion

Understanding how dispersion in analyst's beliefs affects security prices and returns is one of the most fundamental issues in finance. This paper contributes by answering the following question: when is the price of dispersion risk positive? We show that aggregate dispersion effect on security's returns varies across different periods of time. Contrary to previous studies, we look at the price of dispersion risk at different sub-samples: full sample, low, medium and high dispersion months. We find, empirically, that the price of dispersion risk is significantly positive in high dispersion months and significantly negative in low dispersion months. The price of dispersion risk is insignificant and close to zero using the full sample and medium dispersion months. Also, the magnitude of the price of dispersion risk is more pronounced in high dispersion months compared to the low dispersion months.

We construct a general equilibrium model in which analysts of different types have heterogeneous beliefs and provide different forecasts of a macroeconomic factor (aggregate earnings growth). The consumer does not trust either analyst fully, and dynamically adjusts the weight given to each analyst, given the history of their past forecast performance. The model is estimated from 1971-2001, and out-of-sample beliefs of analysts are formulated until 2017. The model provides a positive correlation between the dispersion in the analysts forecasts and the price of dispersion risk. A crucial part of the model's mechanism is that the market weights assigned to lower cash flow beta assets increases in periods of higher dispersion, leading to a large loading on the dispersion risk factor. We provide support for such a flight-to-safety phenomenon in the data.

Table 2.1. Summary statistics of aggregate dispersion (December 1981 to September 2016).

	obs	mean	sd	p10	p25	Median	p75	p90
Full Sample	418	3.51	0.63	2.84	2.98	3.33	3.93	4.53
Low Dispersion Months	55	2.80	0.09	2.70	2.73	2.79	2.87	2.92
Medium Dispersion Months	276	3.35	0.38	2.92	3.03	3.28	3.58	3.87
High Dispersion Months	86	4.48	0.32	4.10	4.32	4.50	4.68	4.81

Aggregate dispersion (in percentage points) is the value-weighted average of stock-level dispersion. Stock-level dispersion is the standard deviation of analyst forecasts of the earning-per-share long-term growth rate (EPS LTG). We define low (high) dispersion months as the months where aggregate dispersion is lower (higher) than the average aggregate dispersion at $t-1$ minus (plus) one standard deviation.

Table 2.2. Analyst Dispersion and Market Excess Return Predictability in the Time-Series.

Panel A: 12/1981 - 12/2005					
Return horizon (in months)	1	6	12	24	36
Aggregate dispersion	-0.622	-6.517**	-16.17***	-29.45***	-36.83*
	(-1.20)	(-2.85)	(-4.24)	(-3.66)	(-2.59)
Constant	2.732	25.94***	62.69***	115.8***	151.6***
	(1.62)	(3.61)	(5.12)	(4.41)	(3.36)
Observations	288	283	277	265	253
Adjusted R^2	0.15 %	8.66 %	25.24 %	40.85 %	33.59 %
Panel B: 12/1981 - 09/2016					
Return horizon (in months)	1	6	12	24	36
Aggregate dispersion	-0.200	-2.906	-6.559	-9.277	-10.18
	(-0.67)	(-1.78)	(-1.91)	(-1.17)	(-0.83)
Constant	1.365	14.62**	32.15**	50.85	65.00
	(1.27)	(2.68)	(2.83)	(1.94)	(1.58)
Observations	417	412	406	394	382
Adjusted R^2	-0.14 %	2.64 %	6.70 %	6 %	4.10 %
Panel C: 01/2006 - 09/2016					
Return horizon (in months)	1	6	12	24	36
Aggregate dispersion	0.333	-0.473	2.380	18.38	31.48**
	(0.53)	(-0.20)	(0.53)	(1.84)	(2.74)
Constant	-0.852	5.745	-2.728	-62.19	-107.9
	(-0.31)	(0.55)	(-0.12)	(-1.27)	(-1.87)
Observations	128	123	117	105	93
Adjusted R^2	-0.59 %	-0.78 %	-0.26 %	14.23 %	32.92 %

The table reports the results of the predictability regression for alternative forecast horizons:

$$r^M_{t,t+h} = \alpha + \beta \times \text{Aggregate Dispersion}_t + \epsilon_{t,t+h},$$

where

$$r^M_{t,t+h} = [(1+R^M_{t+1})\times(1+R^M_{t+2})\times\cdots\times(1+R^M_{t+h})-1]\times 100-[(1+R^f_{t+1})\times(1+R^f_{t+2})\times\cdots\times(1+R^f_{t+h})-1]\times 100.$$

T-statistics are in parenthesis and are adjusted for heteroskedasticity and autocorrelation using the methodology of Newey and West (1987) with the number of lags equal to the forecast horizon.

Table 2.3. Correlation between aggregate dispersion and the standard pricing factors in the asset pricing literature.

Panel A: Full sample

	Aggregate dispersion	$R_m - R_f$	SMB	HML	UMD
Aggregate dispersion	1				
$R_m - R_f$	0.0354	1			
SMB	0.0952	0.205	1		
HML	-0.0319	-0.261	-0.304	1	
UMD	-0.0458	-0.187	0.0643	-0.176	1

Panel B: Low dispersion months

	Aggregate dispersion	$R_m - R_f$	SMB	HML	UMD
Aggregate dispersion	1				
$R_m - R_f$	0.335	1			
SMB	0.186	0.409	1		
HML	-0.133	-0.455	-0.446	1	
UMD	-0.180	-0.467	-0.357	0.286	1

Panel C: Medium dispersion months

	Aggregate dispersion	$R_m - R_f$	SMB	HML	UMD
Aggregate dispersion	1				
$R_m - R_f$	0.0622	1			
SMB	0.149	0.158	1		
HML	-0.158	-0.266	-0.129	1	
UMD	-0.0834	-0.246	-0.153	-0.0567	1

Panel D: High dispersion months

	Aggregate dispersion	$R_m - R_f$	SMB	HML	UMD
Aggregate dispersion	1				
$R_m - R_f$	0.398	1			
SMB	0.0759	0.265	1		
HML	-0.130	-0.220	-0.493	1	
UMD	0.129	0.0371	0.542	-0.477	1

High (low) dispersion months are defined as the months when aggregate dispersion is higher (lower) than the average aggregate dispersion plus (minus) one standard deviation; medium dispersion months are those when aggregate dispersion is in the intermediate range.

Table 2.4. Average Pre-Ranking and Post-Ranking Betas and Deltas (December 1981 - September 2016).

	mean	sd	p10	p25	Median	p75	p90
Panel A: Full Sample							
pre-ranking β	1.09	0.94	0.04	0.49	1.01	1.60	2.27
pre-ranking δ	-0.01	0.24	-0.29	-0.14	-0.01	0.12	0.20
post-ranking β	1.01	0.76	0.06	0.49	0.95	1.47	2.05
post-ranking δ	-0.00	0.19	-0.24	-0.12	-0.01	0.11	0.24
Panel B: Low dispersion months							
pre-ranking β	1.12	1.04	-0.03	0.45	1.03	1.69	2.43
pre-ranking δ	0.00	0.33	-0.37	-0.18	0.00	0.19	0.38
post-ranking β	1.03	0.78	0.06	0.47	0.94	1.52	2.13
post-ranking δ	0.01	0.28	-0.33	-0.17	-0.00	0.17	0.37
Panel C: Medium dispersion months							
pre-ranking β	1.10	0.95	0.04	0.49	1.01	1.61	2.29
pre-ranking δ	-0.02	0.26	-0.32	-0.16	-0.01	0.13	0.28
post-ranking β	1.01	0.77	0.06	0.50	0.96	1.46	2.05
post-ranking δ	-0.01	0.20	-0.26	-0.13	-0.01	0.11	0.25
Panel D: High dispersion months							
pre-ranking β	1.06	0.84	0.09	0.50	0.98	1.52	2.12
pre-ranking δ	-0.00	0.11	-0.13	-0.06	0.00	0.06	0.12
post-ranking β	0.99	0.75	0.07	0.47	0.93	1.44	2.03
post-ranking δ	0.00	0.09	-0.11	-0.05	0.01	0.06	0.12

The table reports the summary statistics of pre-ranking and post-ranking βs and δs for alternative subsamples). Pre-ranking β and δ are obtained each month using lagged one-year rolling data on individual stock returns using the regression:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} \times R_{m,t} + \delta_{i,t} \times \text{Aggregate Dispersion}_{t-1} + \epsilon_{i,t}.$$

We create 100 $\beta - \delta$ portfolios by double-sorting stocks on pre-ranking βs and δs. Post-ranking βs and δs are estimated analogously each month using rolling data for the 100 $\beta - \delta$ portfolios and running the regressions:

$$R_{p,t} = \alpha_{p,t} + \beta_{p,t} \times R_{m,t} + \delta_{p,t} \times \text{Aggregate Dispersion}_{t-1} + \epsilon_{p,t}, \quad \text{for } p = 1, \cdots, 100.$$

We report the the time-series averages of the cross-sectional mean, standard deviation (sd), as well as the 10^{th} to 90^{th} percentiles (p10 to p90) of each variables in the different subsamples. aggregate dispersion is lower then the average aggregate dispersion minus one standard deviation, shown in the figure as the low horizontal line. High (low) dispersion months are defined as the months when aggregate dispersion is higher (lower) than the average aggregate dispersion plus (minus) one standard deviation; medium dispersion months are those when aggregate dispersion is in the intermediate range.

Table 2.5. Average Prices of Market and Dispersion Risk for the Full Sample (December 1981 - September 2016).

	(1)	(2)	(3)	(4)
$\bar{\pi}$	0.00157	0.00149	-0.00189	-0.00204
	(0.67)	(0.65)	(-0.73)	(-0.84)
$\bar{\omega}$		0.00989		0.00851
		(0.92)		(0.76)
$\bar{\phi}^{SMB}$			0.0102**	0.00824***
			(2.86)	(3.98)
$\bar{\phi}^{HML}$			-0.000568	-0.00534**
			(-0.10)	(-2.59)
$\bar{\phi}^{UMD}$			-0.0105**	-0.00683**
			(-2.76)	(-3.08)
Constant	0.00998***	0.0101***	0.0118***	0.0127***
	(6.84)	(7.02)	(6.13)	(8.43)
Adjusted-R^2	0.228	0.501	0.436	0.517

The table reports the time-series averages of the prices of market and dispersion risk from Fama-Macbeth regressions of the 100 $\beta - \delta$ sorted portfolios constructed as described in the footnote of Table 2.4. In each month, t, we run the regression

$$R_t^p = \kappa_t + \pi_t \times \beta_p^{MKT} + \omega_t \times \delta_p + \phi_t^{SMB} \times \beta_p^{SMB} + \phi_t^{HML} \times \beta_p^{HML} + \phi_t^{UMD} \times \beta_p^{UMD} + \epsilon_{t,p},$$

where R_t^p is the value-weighted return of stocks in the p^{th} $\beta - \delta$-sorted portfolio at t, and the regressors β_P^{MKT}, δ_P, β^{SMB}, β^{HML} and β^{UMD}, are the time-series averages of the post-ranking portfolio loadings. We report the time-series average of the estimated prices of market and dispersion risk, $\bar{\pi}$ and $\bar{\omega}$, respectively. T-statistics are reported in parenthesis and are corrected for estimation error as formulated by Shanken (1992).

Table 2.6. Average Prices of Market and Dispersion Risk for Alternative Subsamples.

Panel A: Low Dispersion Months (51 months)

	(1)	(2)	(3)	(4)
$\bar{\pi}$	0.00642	0.00861	0.00600	0.00862
	(1.32)	(1.80)	(1.11)	(1.73)
$\bar{\omega}$		-0.0607***		-0.0632***
		(-4.52)		(-4.48)
$\bar{\phi}^{SMB}$			-0.0101*	0.00164
			(-2.36)	(0.50)
$\bar{\phi}^{HML}$			-0.0198***	-0.00615*
			(-4.31)	(-2.14)
$\bar{\phi}^{UMD}$			0.00381	0.00443
			(1.20)	(1.68)
Constant	0.0106**	0.00869*	0.0121**	0.00890*
	(3.08)	(2.44)	(3.38)	(2.51)
Adjusted-R^2	0.215	0.496	0.464	0.516

Panel B: Medium Dispersion Months (267 months)

	(1)	(2)	(3)	(4)
$\bar{\pi}$	0.00196	0.00188	-0.00216	-0.00224
	(0.69)	(0.67)	(-0.74)	(-0.79)
$\bar{\omega}$		-0.00236		-0.00414
		(-0.20)		(-0.34)
$\bar{\phi}^{SMB}$			0.00730**	0.00852***
			(3.04)	(4.19)
$\bar{\phi}^{HML}$			-0.00504*	-0.00414
			(-2.02)	(-1.77)
$\bar{\phi}^{UMD}$			-0.00728	-0.00823***
			(-1.37)	(-3.41)
Constant	0.00859***	0.00867***	0.0119***	0.0119***
	(5.16)	(5.29)	(6.63)	(7.02)
Adjusted-R^2	0.232	0.504	0.273	0.522

Panel C: High Dispersion Months (78 months)

	(1)	(2)	(3)	(4)
$\bar{\pi}$	-0.0000816	-0.000618	-0.00631	-0.00340
	(-0.01)	(-0.10)	(-0.97)	(-0.51)
$\bar{\omega}$		0.249***		0.248***
		(4.66)		(4.74)
$\bar{\phi}^{SMB}$			0.0116*	0.00650
			(2.35)	(1.40)
$\bar{\phi}^{HML}$			0.0276***	0.00186
			(4.48)	(0.53)
$\bar{\phi}^{UMD}$			0.00190	-0.000195
			(0.38)	(-0.04)
Constant	0.0114**	0.0111*	0.0156**	0.0129**
	(2.69)	(2.62)	(3.42)	(2.74)
Adjusted-R^2	0.226	0.496	0.466	0.506

The table reports the time-series averages of the prices of market and dispersion risk from Fama-Macbeth regressions of the 100 $\beta - \delta$ sorted portfolios constructed as described in the footnote of Table 2.4. In each month, t, we run the regression

$$R_t^p = \kappa_t + \pi_t \times \beta_p^{MKT} + \omega_t \times \delta_p + \phi_t^{SMB} \times \beta_p^{SMB} + \phi_t^{HML} \times \beta_p^{HML} + \phi_t^{UMD} \times \beta_p^{UMD} + \epsilon_{t,p},$$

where R_t^p is the value-weighted return of stocks in the p^{th} $\beta - \delta$-sorted portfolio at t, and the regressors β_P^{MKT}, δ_P, β^{SMB}, β^{HML} and β^{UMD}, are the time-series averages of the post-ranking portfolio loadings. We report the time-series average of the estimated prices of market and dispersion risk, $\bar{pi}$ and $\bar{\omega}$, respectively in the three different subsamples of the data. High (low) dispersion months are defined as the months when aggregate dispersion is higher (lower) than the average aggregate dispersion plus (minus) one standard deviation; medium dispersion months are those when aggregate dispersion is in the intermediate range. T-statistics are reported in parenthesis and are corrected for estimation error as formulated by Shanken (1992).

Table 2.7. Two-State Heterogeneity Model Calibration

Series Used: Real Earnings, Real Consumption,
and Dispersion of Earnings Growth Forecasts
Time Span (Quarterly): 1971-2001

	Analyst 1				Analyst 2			
Drifts:	$\theta_1^{(1)}$	$\theta_2^{(1)}$	$\kappa_1^{(1)}$	$\kappa_2^{(2)}$	$\theta_1^{(2)}$	$\theta_2^{(2)}$	$\kappa_1^{(2)}$	$\kappa_2^{(2)}$
	-0.2440 (0.0194)	0.0828 (0.0289)	0.0280 (0.0103)	0.0280 (0.0103)	-0.2305 (0.0192)	0.0795 (0.0258)	0.0280 (0.0103)	0.0280 (0.0103)
Generator Elements:	$\lambda_{12}^{(1)}$	$\lambda_{21}^{(1)}$	${P_{12}}^{(1)}$	${P_{21}}^{(1)}$	$\lambda_{12}^{(2)}$	$\lambda_{21}^{(2)}$	${P_{12}}^{(2)}$	${P_{21}}^{(2)}$
	0.5061	0.3427	0.1611 (0.0612)	0.0772 (0.0444)	1.3194	0.3727	0.2749 (0.0656)	0.0776 (0.0462)
Volatilities:	$\sigma_{q,1}$	$\sigma_{x,1}$	$\sigma_{x,2}$					
	0.0833 (0.0003)	0.0109 (0.0001)	0.0200 (0.0001)					

Model Fits: $\Delta \log(q)\,(t) = \alpha + \beta \cdot (\theta_1^{(m)}\pi_1^{(m)}(t|t) + \theta_2^{(m)}\pi_1^{(m)}(t|t)) + \epsilon(t),\ m = 1{,}2$

Analyst 1			Analyst 2		
$\hat{\alpha}$	$\hat{\beta}$	R^2	$\hat{\alpha}$	$\hat{\beta}$	R^2
0.0932	1.4885	0.6476	-0.2116	1.8240	0.6737
(0.2224)	(8.8857)		(-0.5248)	(10.0718)	

Dispersion: $d(t,4) = \alpha + \beta \cdot d(\pi^{(1)}(t,4), \pi^{(2)}(t,4)) + \epsilon(t)$

$\hat{\alpha}$	$\hat{\beta}$	R^2
4.1301	0.7190	0.1982
(12.1873)	(4.0921)	

Top Panel: GMM estimates of the following (discretized) model for real consumption, x_t, and real earnings, q_t:

$$x_{t+1} = x_t \cdot e^{(\kappa_t^{(m)} - \frac{1}{2}\sigma_x\sigma_x')\Delta t + \sigma_x\varepsilon_{t+1}} \ ; \ q_{t+1} = q_t \cdot e^{(\theta_t^{(m)} - \frac{1}{2}\sigma_q\sigma_q')\Delta t + \sigma_q\varepsilon_{t+1}}.$$

where $\sigma_q = (\sigma_{q1}, \sigma_{q2})$, $\sigma_x = (0, \sigma_{x,2})$, and $(\theta_t^{(m)}, \kappa_t^{(m)})$ jointly follows a 2-state regime-switching model. The estimates of the quarterly transition probability matrix are shown. The implied generator is $\Lambda^{(m)} = \sum_{i=1}^{\infty}(-1)^{i+1} \cdot \left((P^{(m)}(0.25))^4 - I\right)^i / i$, whose value is estimated using a series approximation of length 10 (see Israel, Rosenthal, and Wei (2001)). The GMM errors include the scores of the likelihood function of each type of agent and the difference in model-implied and historical dispersion in forecasts of Professional Forecasters as described in Appendix D. The $\chi^2(4)$ statistic for the specification test of the model is 7.6341, which has a p-value of 0.1059. **Bottom Panel:** Linear regression for model fits. Standard errors of parameter estimates are in parentheses. Units of measurement are quarterly and in percentage points. T-statistics are in parentheses. All t-statistics are adjusted for heteroskedasticity and autocorrelation using the methodology of Newey and West (1987). Figure 3 (top panel) shows the belief processes of the two agents. The top panel shows the actual and model-implied four-quarter-ahead dispersions of earnings growth, which are in the third regression.

Table 2.8. Average Prices of Market and Dispersion Risk of Ten Test Portfolios for the Full Sample (December 1981 - September 2016).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{\pi}$	-0.918	-1.168	-0.149	0.294	-0.671	-0.810	-0.183	-0.141	-2.035	0.0445
	(-2.52)	(-2.52)	(-0.67)	(0.63)	(-2.66)	(-3.09)	(-1.22)	(-0.19)	(-1.55)	(0.16)
$\bar{\omega}$	-0.954	-5.102	-6.196	4.808	1.365	3.931	2.240	2.775	-15.85	7.289
	(-0.25)	(-1.06)	(-2.69)	(1.02)	(0.43)	(1.43)	(1.26)	(0.39)	(-0.99)	(3.14)
Constant	1.714	1.982	0.836	0.414	1.470	1.607	0.879	0.852	2.747	0.657
	(4.42)	(3.89)	(3.53)	(0.91)	(5.51)	(5.75)	(5.62)	(1.14)	(2.02)	(2.26)
R^2	0.316	0.238	0.560	0.181	0.337	0.141	0.146	0.132	0.308	0.385

The table reports the time-series averages of the price of market and dispersion risk from Fama-Macbeth regressions of the ten test assets: (1) 25 Value Size Portfolios, (2) 25 Net Share Issues Size Portfolios , (3) 10 Size Portfolios, (4) 10 Value Portfolios, (5) 25 Size Investment Portfolios, (6) 100 Size Operating Prof Portfolios, (7) 30 Industry Portfolios, (8) 10 E/P Portfolios, (9) 10 Net Share Issues Portfolios and (10) 25 Book-to-Market and Operating Profitability Portfolios. We obtain value-weighted monthly returns on these portfolios from Ken French's data web site. In each month, t, we run the regression

$$R_t^P = \kappa_t + \pi_t \times \beta_P^{MKT} + \omega_t \times \delta_P + \epsilon_{t,P},$$

where R_t^P is the value-weighted Portfolio return at t and the regressors β_P^{MKT}, and δ_P are the time series average of the post-ranking portfolio market and dispersion risk loadings. We report the time-series average of the estimated prices of market and dispersion risk, $\bar{\pi}$ and $\bar{\omega}$, respectively. T-statistics are reported in parenthesis and are corrected for estimation error as formulated by Shanken (1992).

Table 2.9. Average Prices of Market and Dispersion Risk of Ten Test Portfolios for the Full Sample (December 1981 - September 2016).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{\pi}$	-0.593	-0.972	0.856	2.097	0.0754	-0.421	-0.0923	-1.012	-1.907	1.583
	(-1.05)	(-1.36)	(1.61)	(2.72)	(0.17)	(-1.03)	(-0.35)	(-1.85)	(-1.62)	(3.01)
$\bar{\omega}$	-0.469	-5.122	0.525	-1.871	0.668	2.087	2.443	-2.120	-9.904	-1.281
	(-0.09)	(-0.90)	(0.10)	(-0.35)	(0.18)	(0.82)	(1.80)	(-0.54)	(-1.10)	(-0.45)
$\bar{\phi}^{SMB}$	-0.0218	0.00395	0.0506	0.117	-0.102	0.110	-0.217	0.543	-0.642	-0.585
	(-0.31)	(0.04)	(0.49)	(0.17)	(-1.66)	(1.23)	(-1.44)	(1.53)	(-1.26)	(-2.72)
$\bar{\phi}^{HML}$	0.301	0.482	-0.523	-0.0345	0.549	0.296	-0.192	0.422	-0.674	0.242
	(3.56)	(1.56)	(-0.85)	(-0.37)	(3.23)	(1.18)	(-2.00)	(4.36)	(-1.00)	(3.30)
$\bar{\phi}^{UMD}$	1.987	3.061	-1.398	0.667	1.745	1.695	-0.0886	1.081	0.0496	1.071
	(2.13)	(3.06)	(-1.12)	(1.55)	(2.64)	(3.49)	(-0.29)	(1.72)	(0.03)	(1.72)
Constant	1.322	1.722	-0.151	-1.385	0.672	1.073	0.821	1.724	2.595	-0.881
	(2.29)	(2.33)	(-0.28)	(-1.80)	(1.53)	(2.55)	(3.18)	(3.17)	(2.23)	(-1.67)
R^2	0.536	0.504	0.746	0.881	0.615	0.226	0.401	0.945	0.896	0.663

The table reports the time-series averages of the prices of risk from Fama-Macbeth regressions of the ten test assets: (1) 25 Value Size Portfolios, (2) 25 Net Share Issues Size Portfolios , (3) 10 Size Portfolios, (4) 10 Value Portfolios, (5) 25 Size Investment Portfolios, (6) 100 Size Operating Prof Portfolios, (7) 30 Industry Portfolios, (8) 10 E/P Portfolios, (9) 10 Net Share Issues Portfolios and (10) 25 Book-to-Market and Operating Profitability Portfolios. We obtain value-weighted monthly returns on these portfolios from Ken French's data web site. In each month, t, we run the regression

$$R_t^P = \kappa_t + \pi_t \times \beta_P^{MKT} + \omega_t \times \delta_P + \phi_t^{SMB} \times \beta_P^{SMB} + \phi_t^{HML} \times \beta_P^{HML} + \phi_t^{UMD} \times \beta_P^{UMD} + \epsilon_{t,P},$$

where R_t^P is the value-weighted Portfolio return at t and the regressors β_P^{MKT}, δ_P, β_P^{SMB}, β_P^{HML} and β_P^{umd} are the time-series averages of the post-ranking portfolio loadings. We report the time-series average of the estimated prices of risk, $\bar{\pi}$, $\bar{\omega}$, $\bar{\phi}^{SMB}$, $\bar{\phi}^{HML}$ and $\bar{\phi}^{UMD}$. T-statistics are reported in parenthesis and are corrected for estimation error as formulated by Shanken (1992).

Table 2.10. Average prices of market and dispersion risk of ten test portfolios for alternative subsamples.

Panel A: Low Dispersion Months (51 Months)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{\pi}$	-0.00770	0.0723	0.648	-0.0549	0.184	-0.114	0.828	0.103	0.0861	0.188
	(-0.01)	(0.08)	(0.50)	(-0.05)	(0.20)	(-0.15)	(0.80)	(0.13)	(0.10)	(0.24)
$\bar{\omega}$	-1.648	-6.121	-6.572	-0.759	-3.345	-4.687	-7.701	0.980	-4.640	-0.242
	(-0.64)	(-2.33)	(-0.86)	(-0.22)	(-0.79)	(-1.98)	(-2.28)	(0.24)	(-1.21)	(-0.08)
Constant	1.329	1.233	0.665	1.385	1.139	1.496	0.397	1.251	1.174	1.124*
	(2.71)	(1.85)	(0.62)	(1.41)	(1.75)	(3.21)	(0.49)	(1.78)	(1.58)	(2.07)
R^2	0.272	0.197	0.549	0.445	0.310	0.120	0.203	0.373	0.330	0.317

Panel B: Medium Dispersion Months (267 Months)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{\pi}$	-1.151*	-1.220	-0.500	0.772	-0.843	-0.871*	0.0880	-1.415	-0.697	-0.185
	(-2.00)	(-1.89)	(-0.49)	(1.02)	(-1.83)	(-2.01)	(0.22)	(-1.36)	(-0.77)	(-0.39)
$\bar{\omega}$	-3.377	-6.337	-4.072	-6.494	-0.328	0.423	3.596	-8.698	-2.803	6.647**
	(-0.98)	(-1.60)	(-0.60)	(-1.21)	(-0.12)	(0.23)	(1.50)	(-1.33)	(-0.32)	(2.61)
Constant	1.834***	1.912**	1.128	-0.0709	1.560***	1.571***	0.573	2.067*	1.308	0.833
	(3.41)	(3.28)	(1.17)	(-0.09)	(4.37)	(4.37)	(1.87)	(2.04)	(1.51)	(1.95)
R^2	0.283	0.265	0.551	0.303	0.276	0.135	0.170	0.317	0.313	0.241

Table 2.10. *—Continued*

Panel C: High Dispersion Months (78 months)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{\pi}$	0.717	-0.232	3.022	-0.475	0.183	-0.981	-0.328	0.384	-2.262	-0.129
	(0.51)	(-0.17)	(1.47)	(-0.47)	(0.13)	(-0.81)	(-0.43)	(0.35)	(-1.69)	(-0.14)
$\bar{\omega}$	15.87	15.09	41.97	21.14	20.79	-13.69	8.186	33.74	33.53**	10.92
	(0.73)	(0.90)	(1.58)	(1.17)	(1.74)	(-1.41)	(0.75)	(1.08)	(2.77)	(0.65)
Constant	-0.0941	0.910	-2.691	0.898	0.493	1.657	0.907	0.0215	2.677*	0.667
	(-0.08)	(0.74)	(-1.37)	(1.04)	(0.40)	(1.58)	(1.68)	(0.02)	(2.28)	(0.86)
R^2	0.377	0.248	0.440	0.500	0.336	0.111	0.268	0.407	0.303	0.283

The table reports the time-series averages of the price of market and dispersion risk from Fama-Macbeth regressions of the ten test assets: (1) 25 Value Size Portfolios, (2) 25 Net Share Issues Size Portfolios , (3) 10 Size Portfolios, (4) 10 Value Portfolios, (5) 25 Size Investment Portfolios, (6) 100 Size Operating Prof Portfolios, (7) 30 Industry Portfolios, (8) 10 E/P Portfolios, (9) 10 Net Share Issues Portfolios and (10) 25 Book-to-Market and Operating Profitability Portfolios. We obtain value-weighted monthly returns on these portfolios from Ken French's data web site. In each month, t, we run the regression

$$R_t^P = \kappa_t + \pi_t \times \beta_P^{MKT} + \omega_t \times \delta_P + \epsilon_{t,P},$$

where R_t^P is the value-weighted Portfolio return at t and the regressors β_P^{MKT}, and δ_P are the time series average of the post-ranking portfolio market and dispersion risk loadings. We report the time-series average of the estimated prices of market and dispersion risk, $\bar{\pi}$ and $\bar{\omega}$, respectively in the three different subsamples of the data. High (low) dispersion months are defined as the months when aggregate dispersion is higher (lower) than the average aggregate dispersion plus (minus) one standard deviation; medium dispersion months are those when aggregate dispersion is in the intermediate range. T-statistics are reported in parenthesis and are corrected for estimation error as formulated by Shanken (1992).

Table 2.11. Average Prices of Risk of Ten Test Portfolios for Alternative Subsamples.

Panel A: Low Dispersion Months (51 Months)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{\pi}$	0.184	0.264	0.941	1.220	0.531	0.386	2.496*	-0.601	0.641	0.928
	(0.34)	(0.44)	(0.93)	(0.85)	(1.16)	(0.67)	(2.09)	(-0.53)	(0.65)	(1.07)
$\bar{\omega}$	-2.042	-2.821	-5.151	-1.900	-0.00406	-2.356	-10.56***	1.233	-9.434*	-2.914
	(-1.24)	(-1.58)	(-1.42)	(-0.61)	(-0.00)	(-1.57)	(-3.97)	(0.44)	(-2.17)	(-1.50)
$\bar{\phi}^{SMB}$	-0.159	-0.127	0.104	-0.446	-0.0916	-0.219	-0.628	1.034	-0.347	-0.412
	(-0.46)	(-0.35)	(0.28)	(-0.81)	(-0.24)	(-0.66)	(-1.44)	(1.38)	(-0.63)	(-1.11)
$\bar{\phi}^{HML}$	0.0664	-0.350	-1.765	-0.0319	-0.142	-0.393	-0.522	0.478	1.191	0.00487
	(0.23)	(-1.01)	(-1.37)	(-0.10)	(-0.36)	(-1.33)	(-1.45)	(1.26)	(1.31)	(0.02)
$\bar{\phi}^{UMD}$	1.243*	1.477**	0.378	0.639	1.231*	0.490	1.166*	1.222	1.181	0.249
	(2.34)	(2.99)	(0.80)	(1.08)	(2.51)	(1.70)	(2.48)	(1.37)	(0.71)	(0.56)
Constant	1.179*	1.096	0.408	0.1000	0.817	1.075*	-1.180	1.980	0.613	0.378
	(2.48)	(1.95)	(0.47)	(0.07)	(1.75)	(2.61)	(-1.18)	(1.63)	(0.62)	(0.56)
R^2	0.624	0.516	0.830	0.714	0.585	0.279	0.361	0.734	0.673	0.475

Panel B: Medium Dispersion Months (267 Months)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{\pi}$	-1.407**	-0.938	0.732	2.629**	-0.858	-0.746	-0.00291	-2.110	-3.795**	1.297
	(-2.78)	(-1.70)	(0.93)	(3.05)	(-1.90)	(-1.80)	(-0.01)	(-1.62)	(-2.75)	(1.93)
$\bar{\omega}$	-5.989	-6.080*	2.438	-6.809	-0.0798	-0.631	2.986	-0.486	-13.67	1.293
	(-1.57)	(-2.22)	(0.37)	(-1.24)	(-0.03)	(-0.48)	(1.38)	(-0.09)	(-1.60)	(0.43)
$\bar{\phi}^{SMB}$	-0.0763	-0.0843	-0.0877	-0.0159	-0.138	-0.0577	-0.133	1.174*	0.303	-0.607*
	(-0.46)	(-0.46)	(-0.50)	(-0.02)	(-0.80)	(-0.37)	(-0.46)	(2.44)	(0.53)	(-2.03)
$\bar{\phi}^{HML}$	0.284	0.521	-0.0486	-0.0837	0.298	0.132	-0.151	0.435	-0.159	0.215
	(1.76)	(1.65)	(-0.11)	(-0.40)	(1.24)	(0.63)	(-0.76)	(1.66)	(-0.32)	(1.20)
$\bar{\phi}^{UMD}$	0.705	1.762*	0.0852	-0.102	-0.104	0.891*	-0.162	2.495*	0.121	0.585
	(1.19)	(2.33)	(0.11)	(-0.15)	(-0.17)	(2.49)	(-0.32)	(2.09)	(0.10)	(1.27)
Constant	2.051***	1.617**	-0.0692	-1.979*	1.558***	1.412***	0.697	2.768*	4.368**	-0.653
	(4.79)	(3.21)	(-0.10)	(-2.35)	(4.12)	(4.10)	(1.53)	(2.18)	(3.29)	(-1.04)
R^2	0.582	0.505	0.830	0.683	0.599	0.272	0.363	0.683	0.623	0.443

Table 2.11. —*Continued*

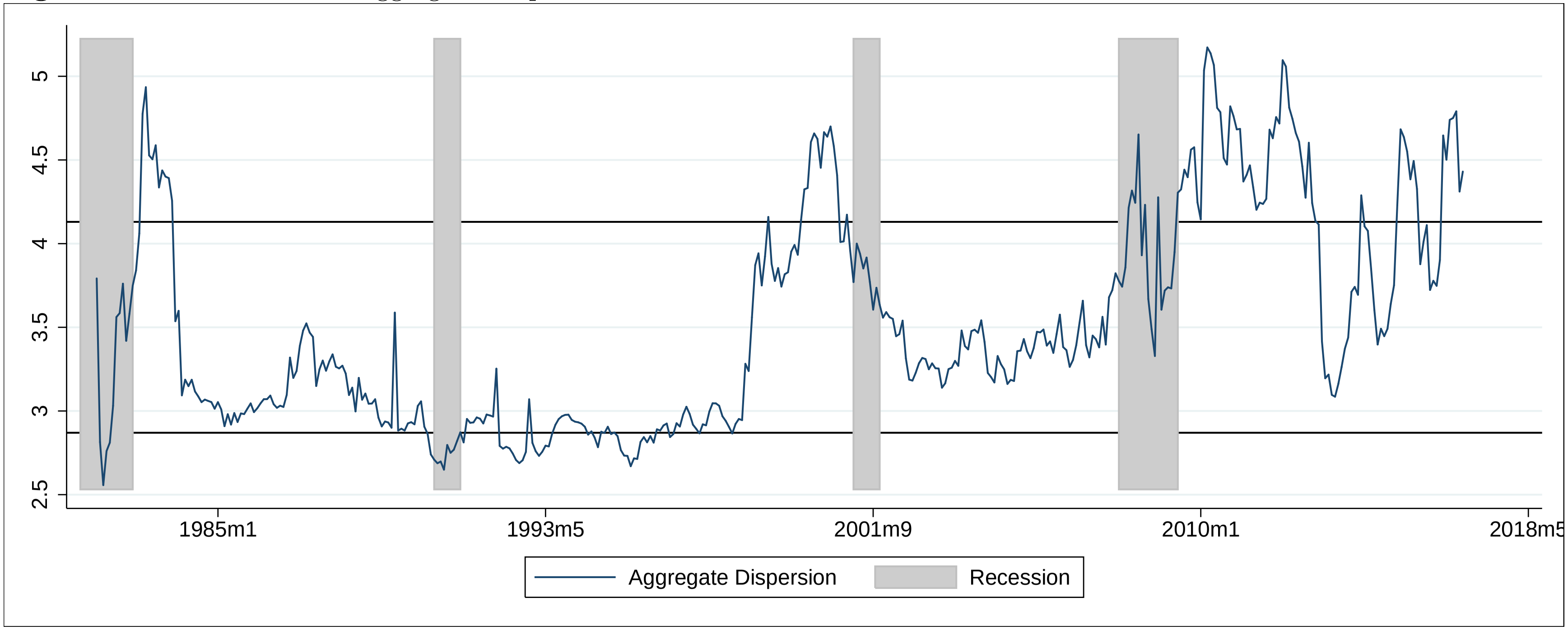
Panel C: High Dispersion Months (78 months)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\bar{\pi}$	0.338	-1.530	1.266	0.976	-0.349	0.831	-0.474	0.922	-0.991	0.157
	(0.38)	(-1.72)	(0.70)	(0.45)	(-0.34)	(1.07)	(-0.51)	(0.36)	(-0.61)	(0.15)
$\bar{\omega}$	13.56	19.96	26.81	18.62	23.83*	-42.23*	11.39	12.42	34.38*	11.92
	(1.10)	(1.65)	(1.84)	(0.68)	(2.37)	(-2.57)	(1.14)	(0.35)	(2.18)	(1.05)
$\bar{\phi}^{SMB}$	0.197	0.465	0.360	1.564	0.142	0.446	-0.128	-1.209	-1.277	-0.0184
	(0.34)	(0.83)	(0.82)	(0.84)	(0.26)	(1.06)	(-0.27)	(-0.47)	(-1.04)	(-0.03)
$\bar{\phi}^{HML}$	0.477	0.195	0.359	0.00531	0.891	1.195*	-0.212	0.178	-1.644*	0.406
	(1.08)	(0.40)	(0.46)	(0.01)	(1.64)	(2.49)	(-0.38)	(0.27)	(-2.38)	(0.91)
$\bar{\phi}^{UMD}$	1.870*	4.138**	3.147	2.184*	3.027**	-4.722**	-0.398	0.797	2.990*	1.239
	(2.48)	(3.31)	(1.14)	(2.00)	(2.88)	(-3.07)	(-0.43)	(0.74)	(2.14)	(1.28)
Constant	0.185	1.931*	-0.941	-0.468	0.813	-0.710	0.989	-0.393	1.389	0.352
	(0.25)	(2.64)	(-0.53)	(-0.23)	(0.98)	(-0.93)	(1.34)	(-0.16)	(0.91)	(0.37)
R^2	0.583	0.467	0.824	0.729	0.602	0.299	0.443	0.704	0.601	0.512

The table reports the time-series averages of the prices of risk from Fama-Macbeth regressions of the ten test assets: (1) 25 Value Size Portfolios, (2) 25 Net Share Issues Size Portfolios , (3) 10 Size Portfolios, (4) 10 Value Portfolios, (5) 25 Size Investment Portfolios, (6) 100 Size Operating Prof Portfolios, (7) 30 Industry Portfolios, (8) 10 E/P Portfolios, (9) 10 Net Share Issues Portfolios and (10) 25 Book-to-Market and Operating Profitability Portfolios. We obtain value-weighted monthly returns on these portfolios from Ken French's data web site. In each month, t, we run the regression

$$R_t^P = \kappa_t + \pi_t \times \beta_P^{MKT} + \omega_t \times \delta_P + \phi_t^{SMB} \times \beta_P^{SMB} + \phi_t^{HML} \times \beta_P^{HML} + \phi_t^{UMD} \times \beta_P^{UMD} + \epsilon_{t,P},$$

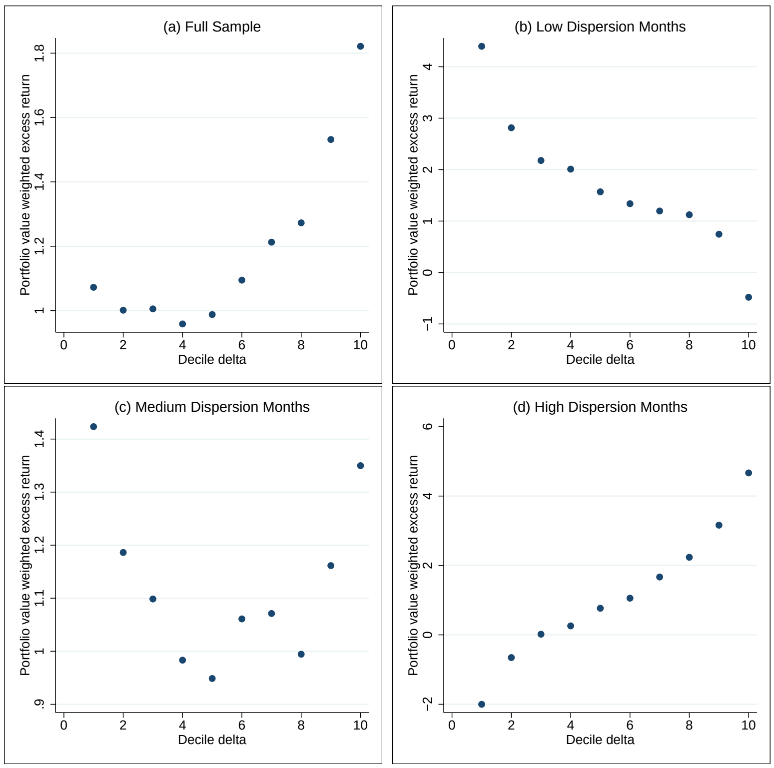
where R_t^P is the value-weighted Portfolio return at t and the regressors β_P^{MKT}, δ_P, β_P^{SMB}, β_P^{HML} and β_P^{umd} are the time-series averages of the post-ranking portfolio loadings. We report the time-series average of the estimated prices of risk, $\bar{\pi}$, $\bar{\omega}$, $\bar{\phi}^{SMB}$, $\bar{\phi}^{HML}$, and $\bar{\phi}^{UMD}$ in the three different subsamples of the data. High (low) dispersion months are defined as the months when aggregate dispersion is higher (lower) than the average aggregate dispersion plus (minus) one standard deviation; medium dispersion months are those when aggregate dispersion is in the intermediate range. T-statistics are reported in parenthesis and are corrected for estimation error as formulated by Shanken (1992).

Figure 2.1. Time-Series of Aggregate Dispersion



The figure plots the monthly aggregate dispersion measured as the value-weighted average of stock-level dispersion. Stock-level dispersion is the standard deviation of analysts' forecasts of the long-term growth rate of earnings-per-share (EPS). High (low) dispersion months are defined as the months when aggregate dispersion is higher (lower) than the average aggregate dispersion plus (minus) one standard deviation; medium dispersion months are those when aggregate dispersion is in the intermediate range. The one standard deviation bands are shown by the horizontal lines.

Figure 2.2. Dispersion Loadings and Portfolio Returns

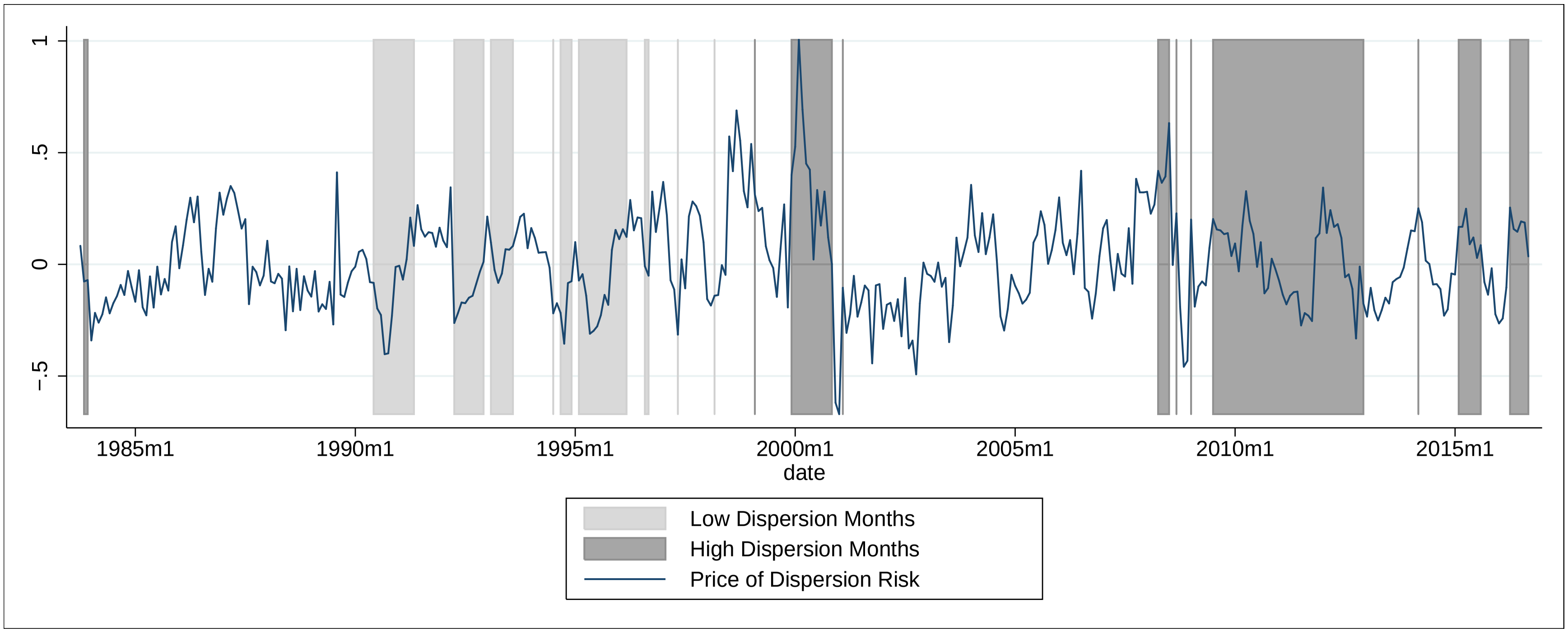


This figure plots the average monthly value-weighted portfolio returns formed by sorting stocks on their pre-ranking δs each month. Pre-ranking β and δ are obtained each month using lagged one-year rolling data on individual stock returns using the regression:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t} \times R_{m,t} + \delta_{i,t} \times \text{Aggregate Dispersion}_{t-1} + \epsilon_{i,t}.$$

High (low) dispersion months are defined as the months when aggregate dispersion is higher (lower) than the average aggregate dispersion plus (minus) one standard deviation; medium dispersion months are those when aggregate dispersion is in the intermediate range.

Figure 2.3. Time-Series of the Price of Dispersion Risk

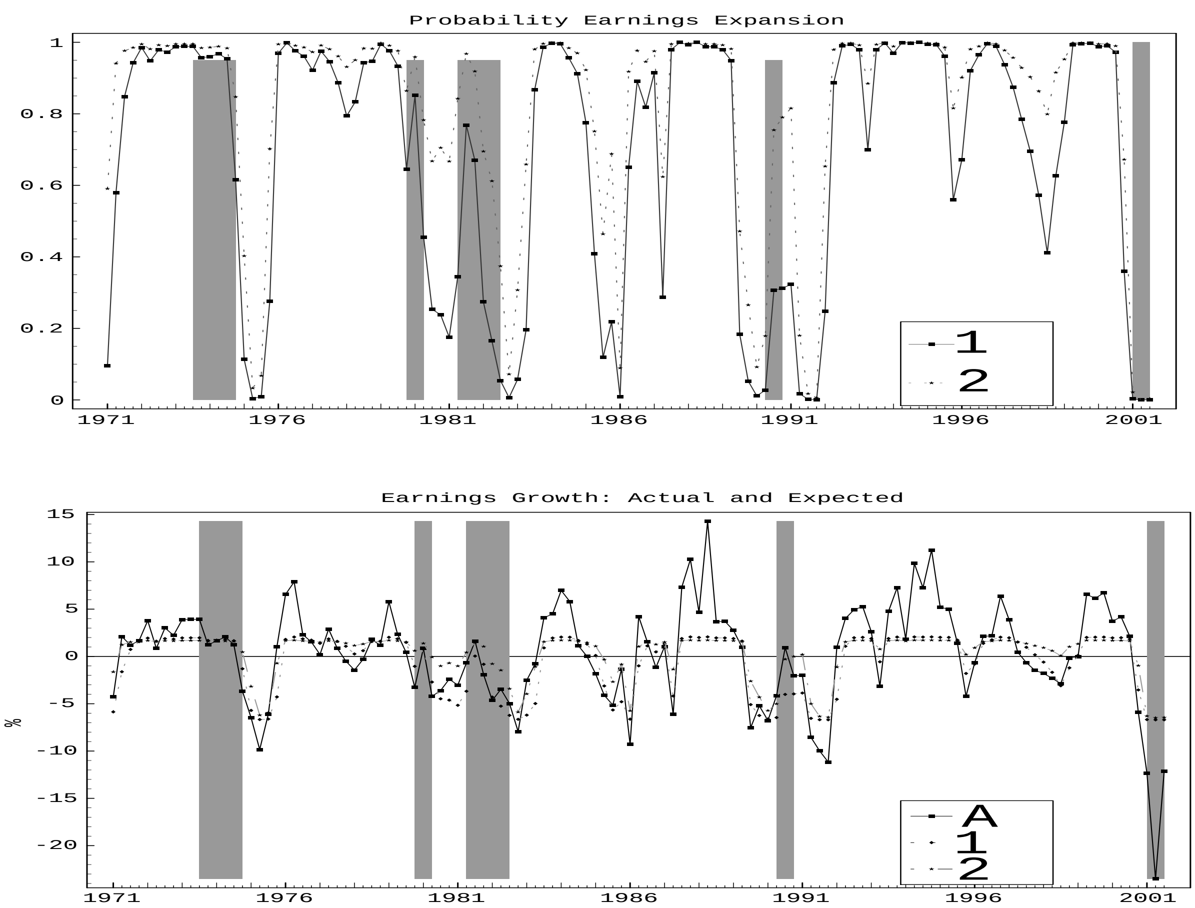


The figure plots the time series of the price of dispersion risk, ω_t. The price of risk is estimated from Fama-Macbeth regressions of the 100 $\beta - \delta$ sorted portfolios constructed as described in the footnote of Table 2.4. In each month, t, we run the regression

$$R_t^p = \kappa_t + \pi_t \times \beta_p^{MKT} + \omega_t \times \delta_p + \epsilon_{t,p},$$

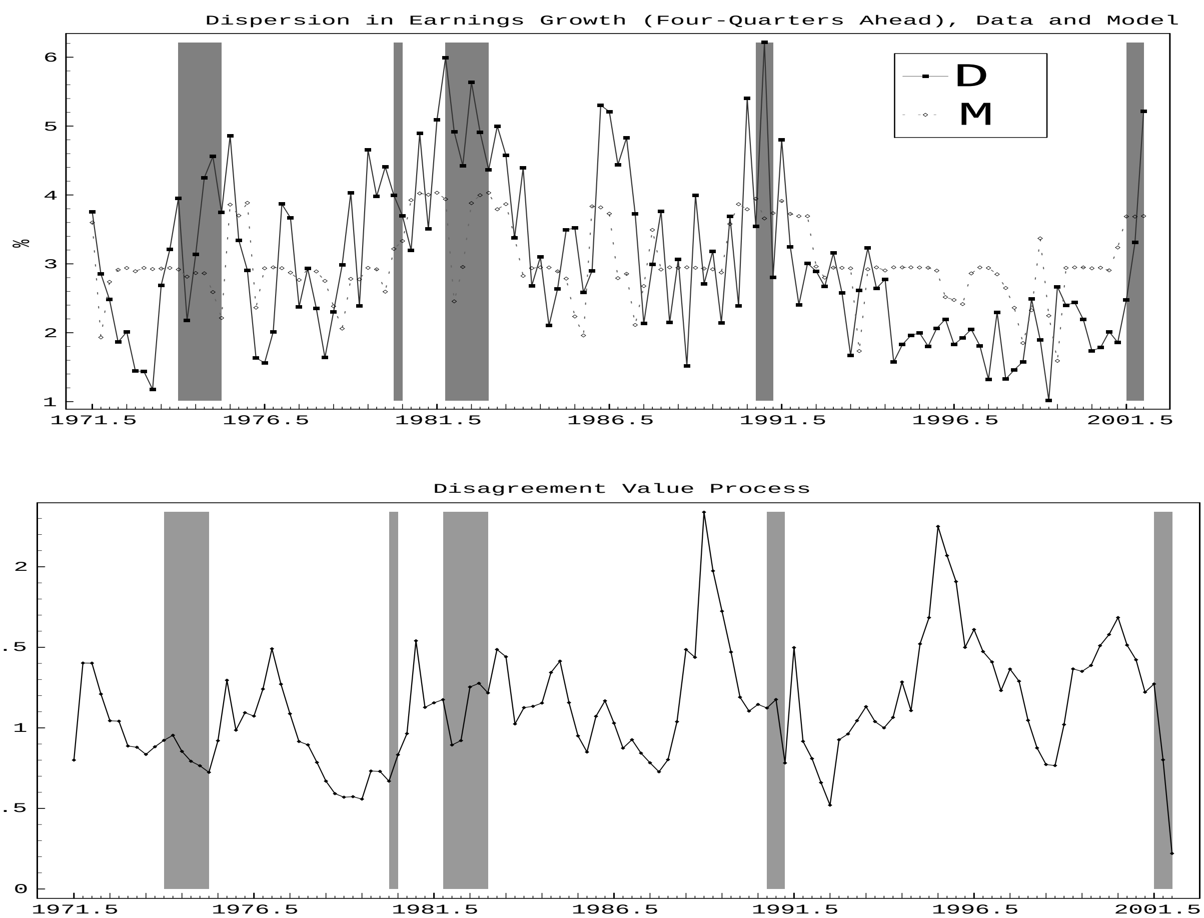
where R_t^p is the value-weighted return of stocks in the p^{th} $\beta - \delta$-sorted portfolio at t, and the regressors β_P^{MKT}, and δ_P, are the time-series averages of the post-ranking portfolio loadings.

Figure 2.4. Investor Beliefs, Expected Growth Rates of Earnings From Calibrated Model (1971 – 2001)



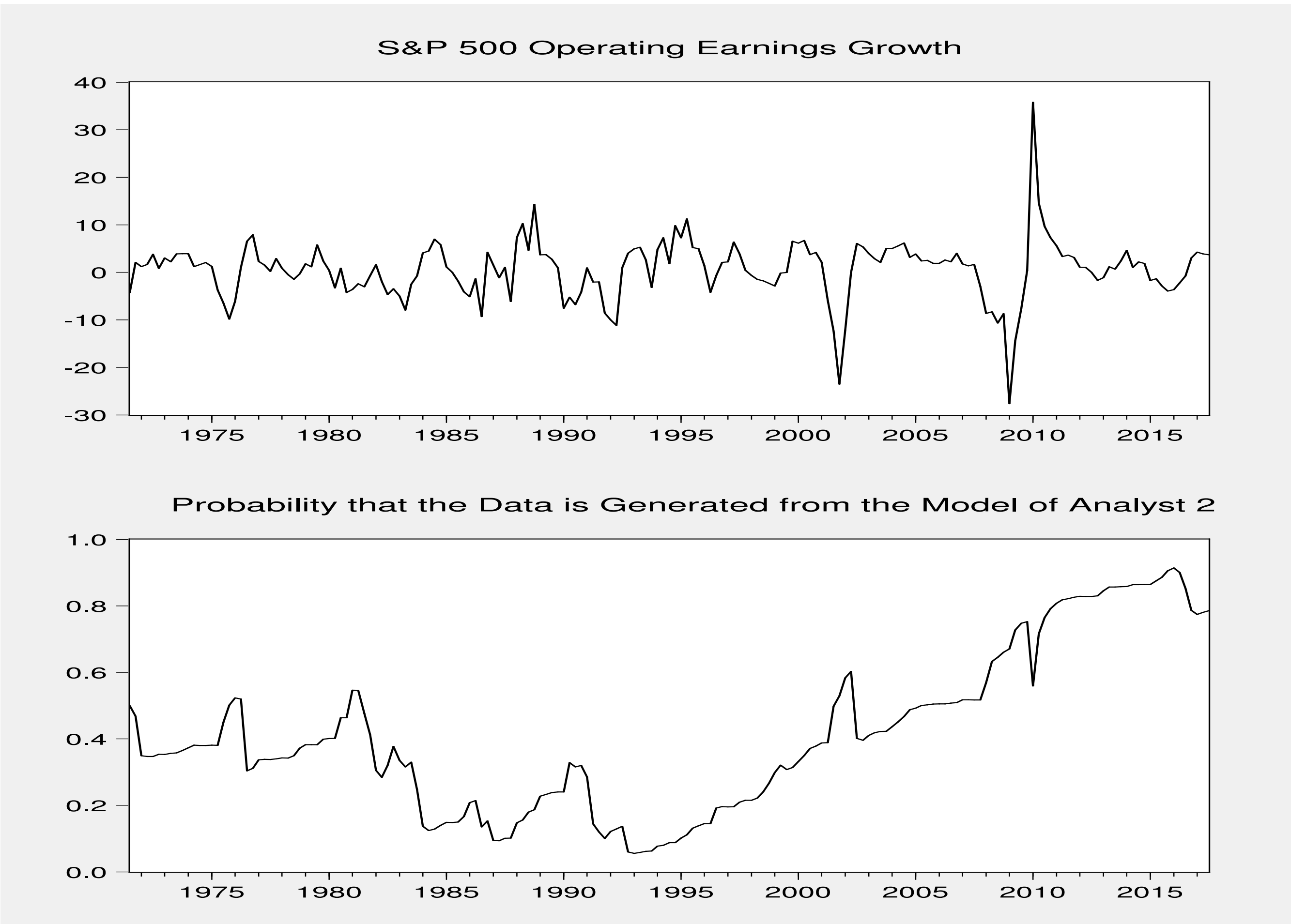
The top panel has the time series of filtered beliefs about real earnings growth of the two types of agents. Filtered beliefs of the two agents are obtained from the discretized version of the belief processes as shown in equation (2.5). The calibrated parameters for each type of agent shown in Table 2.7. The second panel displays the actual and expected earnings growth of the two types of agents using these filtered beliefs.

Figure 2.5. Dispersion in Earning Growth and the Disagreement Value Process (1971 - 2001)



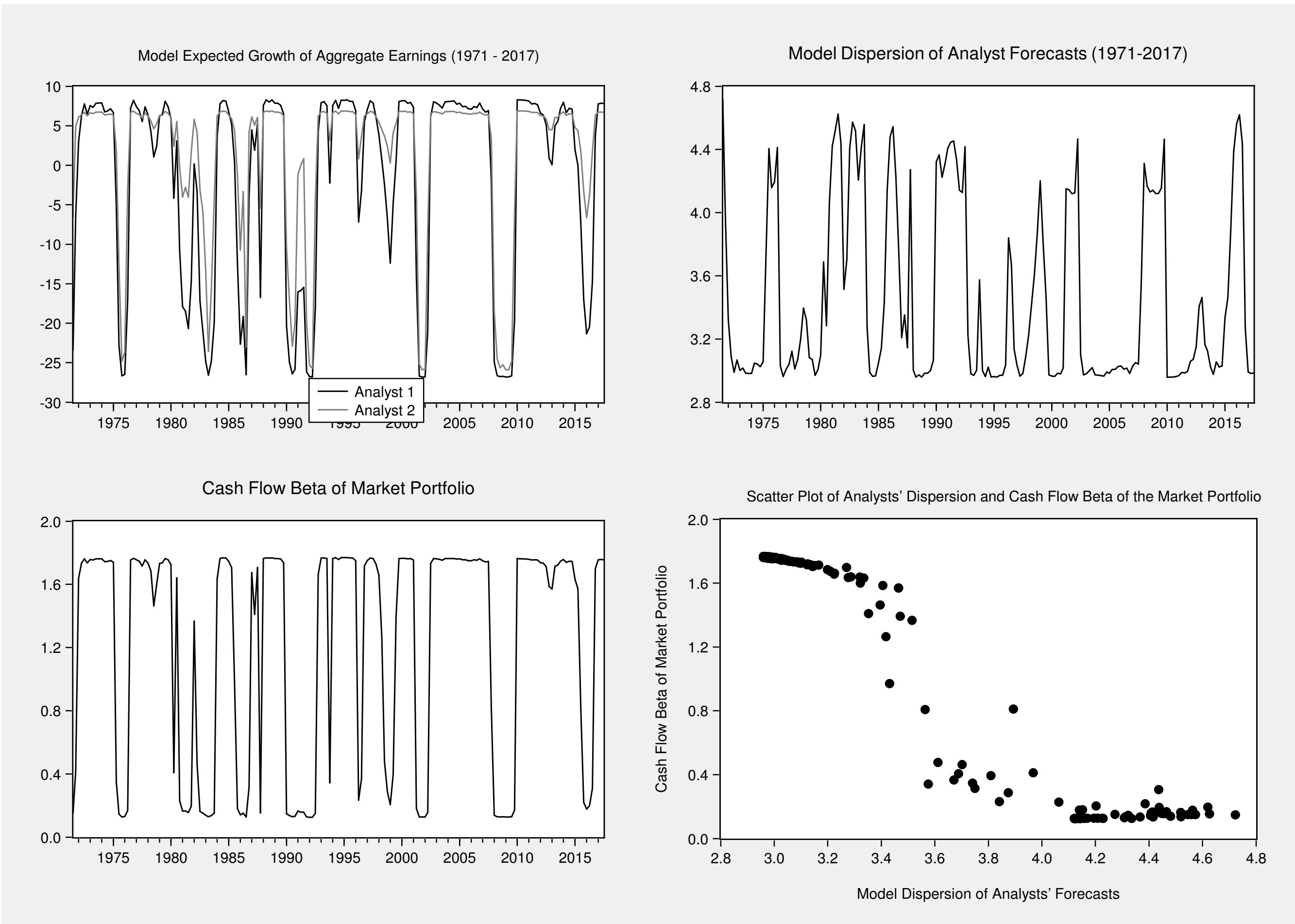
The top panel shows the dispersion of the analysts expectations in the calibrated model with parameters in Table 2.7, as well as the dispersion of forecasted growth from the Philadelphia Fed Survey of Professional Forecasters. The bottom panel shows the disagreement value η_t, which is formulated using the two analyst's beliefs using equation (2.11).

Figure 2.6. S&P 500 Operating Earnings Growth and the Weight Given to the Forecast of Analyst 2 (1971 - 2017)



Historical S& 500 operating earnings growth is obtained from Standard and Poor's. The weight given to Analyst 2 is is formulated in equation. (2.14).

Figure 2.7. Model Forecasted Growth, Dispersion, and the Cash Flow Beta of the Market Portfolio, (1971 - 2017)



Using the parameters in Table 2.7 and realized earnings growth from (1971-2017), we formulate the expected the 1-year ahead forecasted earnings growth of each analyst type, and then report the dispersion as the standard deviation of their forecasts. The cash flow beta of the market portfolio is formulated using the market portfolio weights in Proposition 1.

Figure 2.8. Market Prices of Risk From Simulated 2nd Stage Regression (1971 - 2017)

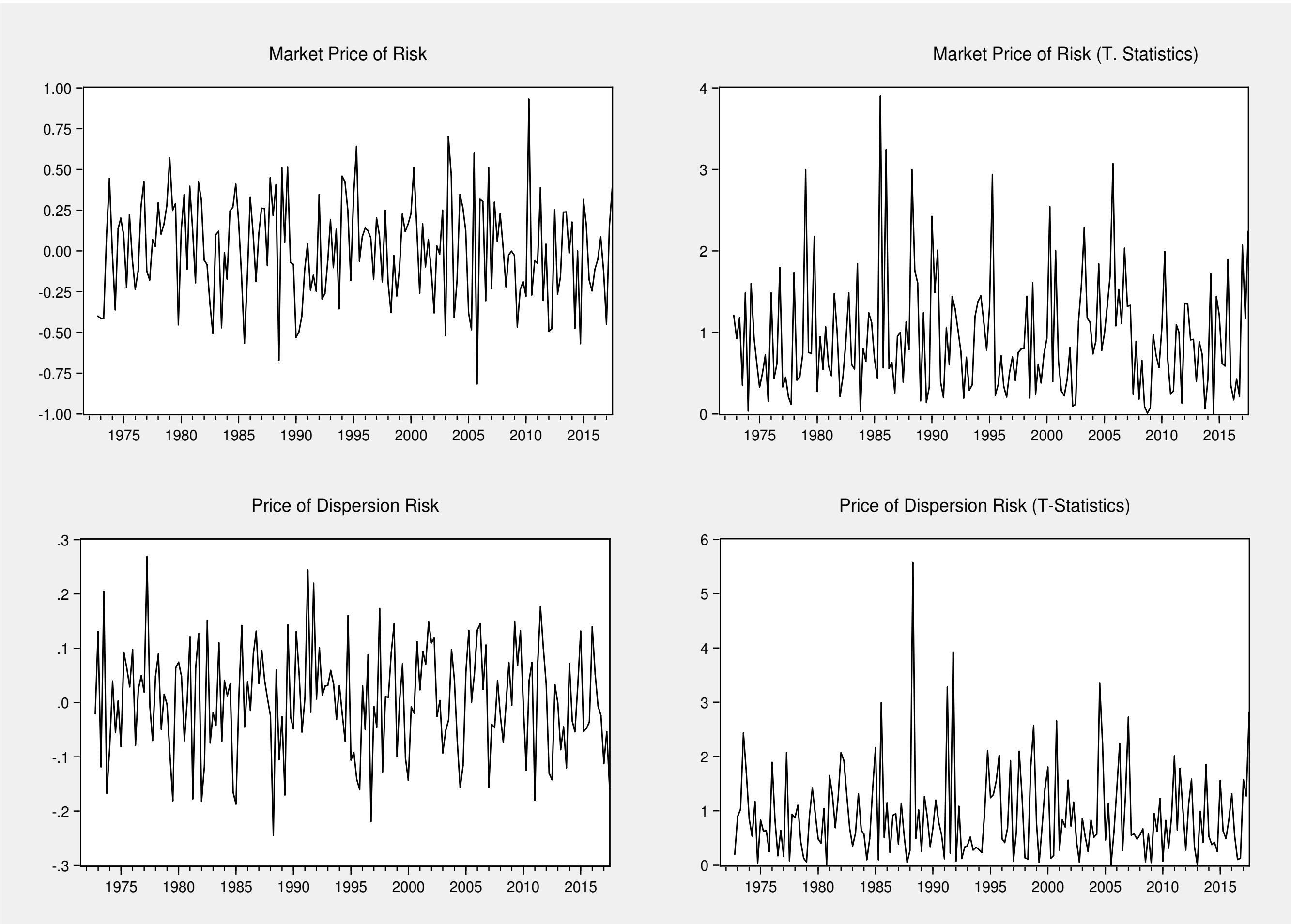
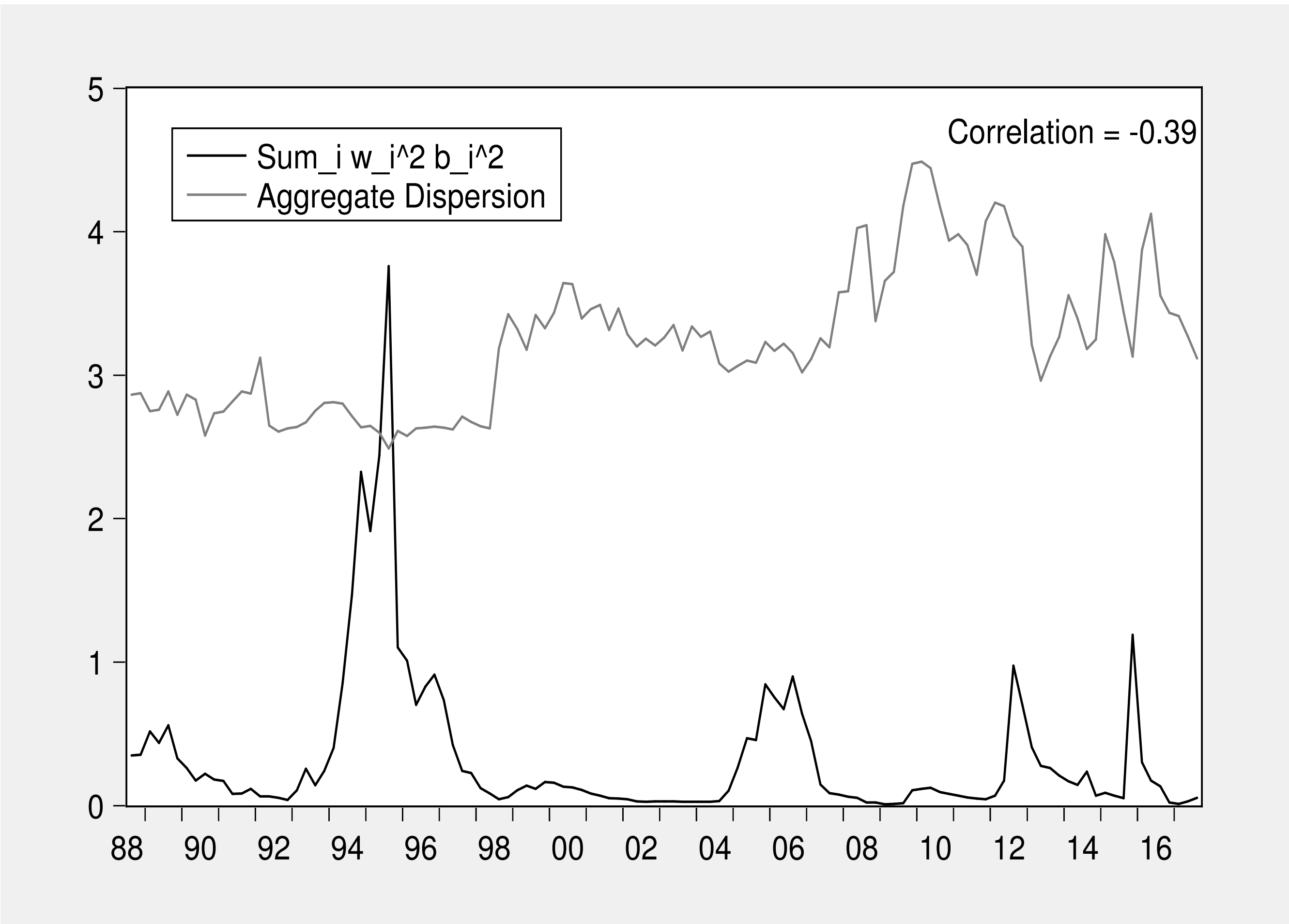


Figure 2.9. The Flight-to-Safety effect in the data



The dispersion series is the value-weighted average of the stock-level dispersion. For each stock, i, the cash flow beta, b_i is estimated using 5-year rolling windows of firm level earnings growth on aggregate earnings growth. The weight, w_i is the market capitalization weights of each stock in the CRSP database.

Chapter 3

Does Analysts' Experience Create Price Reaction?

3.1 Introduction

There is a large and expanding literature that documents that analysts' beliefs affect asset prices. The majority of prior studies treats analysts equally and concentrates on the analysts' consensus forecasts[1]. This chapter questions the view that all analysts are equal and develops the idea that analysts may have different strategic behaviour to influence the market. The main contribution is to provide evidence that the market assigns different weights to different analysts and to show that more experienced analysts have more significant impact on asset prices and trading activity.

First, I observe that the frequency of small positive forecast errors is larger than the frequency of small negative forecast errors for experienced analysts[2]. I do not detect this characteristic for inexperienced analysts. Second, I show that firms followed by experienced analysts display a more pronounced post-earning announcement drift and a higher trading activity than firms followed by inexperienced analysts. Combining these two empirical facts, I infer that experienced analysts know how to impact the market. A possible explanation is

[1] for example Diether et al. (2002)

[2] This has been first studied by Abarbanell and Lehavy (2003). The authors analyze the distribution of the forecasts errors for all analysts.

that they do so by adjusting their forecasts, which allow them to surprise the market and generate more trades.

I start the empirical study by sorting analysts based on their general experience, defined as the number of quarters for which the analyst supplied at least one forecast. I call experienced (inexperienced) analysts, analysts that have the highest (lowest) general experience. By taking a closer look at the distribution of the forecast errors for experienced and inexperienced analysts, I notice the high occurrence of small positive forecasts errors compared to small negative forecast errors for experienced analysts. This finding contradicts the rational expectations models where agents expectations are assumed not to be systematically biased. I do not discern this property for inexperienced analysts.

Then, I classify firms into two groups based on the number of experienced and inexperienced analysts that are following them[3]. I stress that the stock choice decision made by analysts is not made randomly[4]. This firm categorization allows us to examine the post-earnings announcement returns as well as the trading activity for the two different sets of firms on the announcement period. I show that the average daily returns at the earning announcement day t as well as at the $t+1, \ldots, t+10$ following days are significantly higher for firms that are mainly followed by experienced analysts compared to firms that are mainly followed by inexperienced analysts. The gap becomes wider as the holding period increases. I also see that for both groups, the returns continue to drift up (down) for good (bad) news. Note that the post-earnings announcement drift is more pronounced for firms followed mainly by experienced analysts.

Moreover, there is strong evidence that high absolute value of unexpected earnings generates higher abnormal trading volume for both firm categories at the day of the announcement as well as the seven following days. However, the high trading volume is, clearly, more pronounced for firms followed by experienced analysts.

[3] If the number of experienced analysts exceeds the number of inexperienced analysts, the firm is considered followed mainly by experienced analysts and vice versa.

[4] see Bradshaw (2011)

The empirical finance literature offers several research papers that examine the impact of sell-side analysts' earnings forecasts on prices and trading volume [5]. Given the importance of the role played by sell-side analysts, it is interesting to study what analysts do and how they differ from each other in analyzing and using financial information. This chapter contributes to a growing body of research that investigates how and whether some analysts are better than others. For example, Mikhail, Walther, and Willis (1997) find a statistically significant negative relationship between the absolute value of analyst quarterly forecast errors and firm-specific experience. Using the I/B/E/S Detail History database, Clement (1999) finds that forecast accuracy is positively associated with analysts' experience and employer size and negatively associated with the number of firms and industries followed by the analyst. Jacob, Lys, and Neale (1999) argue that analysts' aptitude and brokerage house characteristics are associated with forecast accuracy. Jackson (2005) uses data from the Australian equity market and provides evidence that optimistic analysts generate higher trading volume for their firm. De Franco and Zhou (2009) find evidence that CFA Charterholders' forecasts are more accurate if we control for the day of the forecast and less accurate if we do not. More recently, Michaely, Rubin, Segal, and Vedrashko (2018)) find that the market reacts to the more accurate average forecast generated by high-quality analysts rather than to the consensus forecast. This chapter complements this literature stream by emphasizing that experienced analysts may have more significant impact on prices and trading volume.

Section 2 of this chapter presents the data used and categorizes the analysts based on their general experience measure. Section 3 distinguishes between the firms that are followed by experienced analysts and firms that are followed by inexperienced analysts and reports the

[5] For example: Fried and Givoly (1982) find an association between unexpected earnings and share price changes. Stickel (1992) shows that earnings forecasts of Members of the Institutional Investors All-Americans Research Team impact prices more than others. Cooper, Day, and Lewis (2001) find that leads analysts have more influence on the decisions of investors and have a greater impact on stock prices than follower analysts. Irvine (2003) and Demiroglu and Ryngaert (2010) document that analysts initiations result in positive price impact. Derrien and Kecskés (2013) show that changes in analyst coverage cause changes in corporate policies. Li and You (2015) find that stocks market reacts positively to analysts' coverage. The authors show that the investors' recognition, measured by the change in the breath of ownership, has the highest explanatory power on the market reaction to coverage changes.

post-earnings announcement returns as well as the abnormal volume for both firm groups. Section 4. discusses the results and section 5 concludes this study.

3.2 Data description

This study includes firms listed in both the Institutional Brokers Estimate System (I/B/E/S) Detail History file and Center for Research in Securities Prices (CRSP) daily file during the period from January 1984 to January 2018. The data on analysts' earnings quarterly estimates as well as the actual quarterly earnings are taken from I/B/E/S Detail History file. Daily returns and stocks characteristics (volume, shares outstanding ...) are drawn from CRSP daily Stocks which includes NYSE, AMEX, and Nasdaq stocks. Following Michaely et al. (2018), I keep firms that are followed by at least four analysts to avoid the small sample bias.

3.2.1 General Experience

To construct the primary variable of interest, the general experience measure, I use the I/B/E/S Detail History database at the quarterly frequency[6]. I define the analyst's general experience as the number of quarters for which the analyst supplied at least one forecast. Consistent with prior studies (Clement (1999), Clement and Tse (2005)), I only count quarters where the forecast is made at least one month prior the earnings announcement. Based on the general experience measure, I group analysts into Inexperienced and Experienced categories: Experienced (Inexperienced) analysts are analysts with general experience higher (lower) than the median[7].

[6]I run the same exercise at the annual frequency.

[7]I omit the first four years of data because, on average, analysts with more than four years of experience are considered experienced analysts. This allows analysts to build experience in the sample.

3.2.2 Descriptive Statistics

Table 3.1 conducts a simple comparison between experienced and inexperienced analysts' characteristics. First, large firms employ more experienced analysts than inexperienced analysts on average. Table 3.1 reports the average number of each analyst type in every brokerage house category and shows that the number of experienced analysts is 35 % higher than the number of inexperienced analysts in big brokerage houses. Second, experienced analyst follows more firms than inexperienced analysts on average. Table 3.1 lists the firm coverage for every analyst type and reports that experienced analyst follows 35 % more firms than inexperienced analysts. I define the firm coverage as the number of firms followed by the analyst. Third, Experienced analysts always beat the inexperienced analysts by providing the lowest absolute forecast error. Table 3.1 presents the absolute forecast errors[8] as well as the forecast errors for experienced and inexperienced analysts. The absolute forecast error is the absolute difference between the actual annual earning and the analyst forecast estimate, divided by the share price at the beginning of the calendar quarter. Similar to Abarbanell and Lehavy (2003), I notice that for both types of analysts, the percentage of positive errors is higher than the percentage of negative errors, suggesting apparent analysts' pessimism. Table 3.1 shows that the percentage of positive (negative) forecast error equals 58% (30%) for experienced analysts and equals 54% (34%) for inexperienced analysts. I infer that experienced analysts are more pessimist than inexperienced analysts. This fact contradicts numerous research studies where authors document that analysts generally produce optimistic forecasts (see Brown (1993) and Kothari (2001)). I also notice, an interesting characteristic of the forecast error sample of both analyst types: 11 percent of the observations have a value of exactly zero.

[8] which is the one closest to the announcement day

3.2.3 Standardized Unexpected Earnings: SUE

This section examines the distribution of the forecast error for experienced and inexperienced analysts. This exercise is motivated by the research paper of Abarbanell and Lehavy (2003). The authors document an interesting feature of the forecast error distribution of all analysts, which they refer to as the middle asymmetry property. In particular, they find that the frequency of small positive relative to small negative errors increases as forecasts errors become smaller in absolute magnitude.

To run this empirical investigation, I calculate the standardized unexpected earnings (SUE) for both type of analysts as the quarterly actual earnings per share (as reported in I/B/E/S) minus the average forecast provided by experienced analysts or inexperienced analysts, scaled by the price at the beginning of the quarter.

$$\text{SUE}_{i,t} = \frac{(AE_{i,t} - F_{i,t})}{\text{price}_{t-1}} \tag{3.1}$$

where $AE_{i,t}$ is the firm actual earnings, $F_{i,t}$ is the average forecast provided by experienced analysts (inexperienced analysts). Price_{t-1} is the stock price at the beginning of the quarter.

I run a similar analysis to Abarbanell and Lehavy by examining the distribution of the forecast errors for both types of analysts. The figure 3.1 presents the frequency of the forecast's errors within -1% and 1%. The middle asymmetry, as defined by Abarbanell and Lehavy, is discernible for experienced analysts. In particular, Figure 3.1 Panel (a) shows that the frequency of small positive forecast errors is larger than the frequency of small negative forecast errors. Table 3.2 reports that the difference between the proportion of small positive and small negative forecast errors is significant. Note that the rational expectations models contradict this finding as these models emphasize the idea that agents' expectations are assumed not to be systematically biased. I do not identify this property for inexperienced analysts. Figure 3.1 Panel(b) displays the reverse property of the distribution. There is a high occurrence of small negative forecast errors compared to small positive forecast errors. It is also important to note that the difference between the forecast error's distributions is only observed using the quarterly forecast and actual earnings per share. Annual data does not show the same discrepancy in the forecast error distribution of experienced and inexperienced analysts. Finally, I notice again the high frequency of exactly zero observations in Figure 3.1.

3.3 Who is Following the Firm?

In the following section, I categorize firms based on the number of experienced and inexperienced analyst following them in order to draw conclusions about average returns, abnormal volume for the two categories of firms. If the number of experienced analysts exceeds the inexperienced analysts, the firm is considered followed mainly by experienced analysts and vice versa. As noted in the review of Bradshaw (2011), I emphasize that analysts must decide what stocks to cover. The stock choice decision is not made randomly.

Table 3.3 summarizes the characteristics of firms in the two categories described above. The sample is heavily tilted towards big stocks. As Hong, Lim, and Stein (2000) note, the smallest firms are not covered by I/B/E/S. The average firm size is slightly higher for firms that are followed mainly by experienced analysts compared to firms that are followed mainly by inexperienced analysts, suggesting that experienced analysts follow larger firms than inexperienced analysts.

3.3.1 Post-Earnings Announcement Returns

Now, I turn my attention toward the post-earnings announcement returns for both firm categories. The goal is to examine how return around earnings release differs for firms that are followed by experienced and inexperienced analysts.

Previous empirical studies document that returns drift in the direction of the earning surprise in the days (months) following earning announcements (see for example: Ball and Brown (1968), Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989)). I do not target to explain the post-earnings announcement drift, but I aim to document the difference in returns for firms followed by experienced analysts and firms that are followed by inexperienced analysts. This will allow us to study the impact of experience on stock prices and returns.

Table 3.4 reports the average return at the earning announcement day t, as well as, at the $t+1, \cdots, t+10$ following days. The average daily returns are higher for firms that are followed mainly by experienced analysts. The gap becomes wider as the holding period increases. The gap is significant starting from four trading days post announcement. It starts at 0.125% at $t+4$ to reach 0.249% at $t+10$.

To capture the post-earnings announcement drift, I refer to the SUE calculated previously. For both firm groups, I divide firms based on the sign of SUE. Table 3.5 reports the average return, for both firm categories, at the earning announcement day t, as well as, at the $t+1, \cdots, t+10$ following days for positive and negative SUE. For both firm categories, the returns continue to drift up for good news and down for bad news. However, the magnitude of the drift, in absolute value, is higher for firms followed by experienced analysts compared to firms followed by inexperienced analysts. I conclude that the post-earnings announcement drift phenomenon is more pronounced when experienced analysts are more uncertain about the firm's performance. This finding motivates the idea that investors may be more confused when the surprise (forecast errors) arises from experienced analysts compared to inexperienced analysts. To test this intuition, it is important to examine, carefully, the degree of uncertainty in the market and the experienced analysts' forecasts errors. Zhang (2006) and Francis, Lafond, Olsson, and Schipper (2007) analyze all analysts sample and find a positive relation between uncertainty and post-earnings announcement drift.

3.3.2 Abnormal Volume

The following section analyzes the relationship between the trading volume and SUE for firms that are followed by experienced analysts and firms that are followed by inexperienced analysts. The goal is to explore the impact of analysts' experience on trade generation.

I begin by calculating the percentage of a firm's outstanding shares traded on any particular day as the firm's volume at t, divided by its shares outstanding. Following Bamber (1987), I use a firm-specific measure of abnormal volume. First, I calculate the median daily percentage of firm i's shares traded on the non-announcement period, where the announcement period defined as the 15 days centered on the earnings announcement day. Second, I calculate the abnormal volume as the difference between the actual percentage of shares traded on the announcement day and the median non-announcement volume. As mentioned by Garfinkel and Sokobin (2006), I subtract the median trading activity over the non-announcement period to make sure that the high turnover observed in the announcement window is not associated with a high turnover overall.

For every group of firms, I sort firms based on the consensus absolute SUE into four subgroups. The first subgroup contains low absolute SUE, and the fourth subgroup contains high absolute SUE[9].

Table 3.6 analyzes the relation between the abnormal volume and the absolute SUE. For both categories of firms, the abnormal volume is an increasing function of the absolute SUE. However, the increase is more pronounced for firms followed mainly by experienced analysts. The volume difference between the highest and the lowest SUE quartile equals to 0.233% for firms followed by inexperienced analysts and to 0.491% for firms followed by experienced analysts.

It is worth mentioning that experienced analysts, and analysts in general, have many incentives to generate higher trading volume. Previous studies associated trading volume with analyst's performance and compensation (Cooper et al., 2001) and with investor's

[9] In order to maintain the comparability of the different subgroups, I use the consensus SUE to rank firms.

attention (Barber and Odean, 2007), where trading volume is a proxy for whether investors were paying attention to a firm.

Abnormal Volume and Firm Size

I now focus on the size and the magnitude of the trading activity for both firm categories associated with the quarterly earnings announcement. In the first exercise, I rank both categories of firms into three groups depending on their market capitalization. Then, I report the average abnormal volume for firms across the six sub-samples on the announcement day. Table 3.7 Panel A, reports the sorting results for firms that are followed by inexperienced analysts. I do not distinguish a significant trading difference among small, medium, and large firms. Panel B reports the sorting results for firms that are followed by experienced analysts. I observe that large firms generate higher trading volume than the other sub-groups. In particular, the average abnormal volume equals to 1.040 and 0.888 for large and small firms, respectively.

In the next exercise, I rank every firm in each size groups, shown in the previous exercise, into four quartiles based on their consensus surprise. In total, I obtain 24 sub-groups of firms, 12 for each firm type. Table 3.8 shows that as the absolute value of unexpected earning increase, large and medium-sized firm's quarterly announcements on average generate a more significant increase in trading than do smaller firm's announcement. This result holds for firms followed mainly by experienced analysts. In particular, for these firms, the difference between the average abnormal volume for high absolute SUE and low absolute SUE equals to 0.403 for small firms, 0.546 for medium firms and 0.556 for large firms. This is counter-intuitive as small firms are less likely to be affected by pre-disclosure information, and there is more pre-disclosure information for large firms (see Bamber (1987)). However, I observe that the trading volume remains at the same levels for firms followed mainly by inexperienced analysts. Table 3.8 also shows that the higher the absolute SUE, the higher will the abnormal volume be. This is true and significant, especially for firms followed mainly by experienced analysts.

Abnormal Volume and Duration

To analyze the duration of the abnormally high trading volume, I calculate the abnormal trading volume for firms followed mainly by experienced analysts and for firms followed mainly by inexperienced analysts for 15 days period centered on the announcement day. Table 3.9 reports that the trading volume reached the highest level in the day of the announcement as well as the following day for both firm categories. In the day of the earnings announcement (following day), the abnormal trading volume equals to 0.844 and 0.915 (1.172 and 1.306) for firms followed by inexperienced analysts and firms followed by experienced analysts, respectively.

Abnormal Volume: Lowest and Highest SUE Quartiles

Similar to the previous section, I sort firms into three groups based on their market capitalization then I sort firms based on the absolute SUE level into four quartiles. Table 3.10 presents the sorting results. To make the reading of the table easier, I plot the results. Figure 3.2 graphs the smallest versus the highest Absolute SUE quartiles trading volume for firms followed mainly by experienced analysts and firms followed mainly by inexperienced analysts for 15 days period centered on the announcement day. There is strong evidence that larger absolute value of unexpected earnings generates higher abnormal trading volume for both firm categories. However, the difference between the volume in the highest and the lowest Absolute SUE plotted in Figure 3.2 Panel B, is more pronounced for firms followed by experienced analysts.

3.4 Discussion

At this stage, I show that the post-earnings announcement drift is more pronounced for firms followed by experienced analysts. These firms also generate higher trading activity than other firms. I also mentioned earlier that the forecast error distribution of experienced analysts exhibits an important feature: The frequency of small positive forecast errors is larger than the frequency of small negative forecast errors. I do not observe the same characteristic for forecast error distribution of inexperienced analysts. Combining these two empirical facts, I infer that experienced analysts may know how to impact the market. A possible explanation is that they do so by adjusting their forecasts, which allow them to surprise the market and generate more trades. It is also interesting to investigate the factors that motivate the analysts to induce a downward bias in their forecasts. A possible explanation is documented by Hilary and Hsu (2013). The authors show that low-balling helps analysts in maintaining a good relationship with firms' managers, as firms' managers can beat those downward biased forecasts. Therefore, analysts may have better access to internal information, leading to more accurate forecasts used to generate more consistent downward biased forecasts. To confirm this intuition, this practice should be more accessible for experienced analysts. One need to show that building a solid network with firm managers depends on the analyst's experience.

3.5 Conclusion

During the past several decades, the interest in exploring the role of sell-side analysts in capital markets has grown extensively among academics, investors, and regulators. This chapter focuses on the differences among analysts based on their general experience measure and answers the following question: Does analysts' experience creates price reaction? This chapter shows that, for experienced analysts, the frequency of small positive forecast errors is larger than the frequency of small negative forecast errors. Also, firms followed by experienced analysts display more pronounced post-earning announcement drift and higher trading volume at the announcement day as well as the following days than other firms. Therefore, experienced analysts have more significant impact on the prices and trade volume. They do so by adjusting their forecasts and reporting downward biased earnings forecasts.

Table 3.1. Comparison Between Experienced and Inexperienced Analysts' Characteristics.

	Analysts		
	inexperienced	experienced	Difference
Brokerage Firm Size			
1 small	2.03	2.01	-1.31 %
2	10.94	9.54	-14.63 %***
3 big	69.51	107.48	35.32 %***
Firm Coverage	6.06	9.31	34.96 %***
Forecast Error			
SUE	0.00215	0.00178	-0.00037***
Abs.SUE	0.00868	0.00706	-0.00163***
% Positive Forecast Error	54.08 %	58.50 %	
% Negative Forecast Error	34.24 %	30.60 %	
% Zero Forecast Error	10.93 %	10.91 %	

This table conducts a comparison between experienced and inexperienced analysts' characteristics. The sample period is from January 1988 to January 2018. General experience is the number of quarters for which the analyst supplied at least one forecast during the first two months of the quarters. We group analysts into Inexperienced and Experienced categories based on their general experience measure. Experienced (Inexperienced) analysts are analysts with general experience higher (lower) than the median. *Brokerage House Size* is the number of analysts in the analyst's brokerage house. *Firm Coverage* is the number of firms covered by the analysts. *The Forecast Error (SUE)* is the difference between the actual annual earnings and the analyst forecast estimate, divided by the share price at the beginning of the calendar quarter. *Abs.SUE* is the absolute forecast error. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 3.2. Percentage of Small Positive and Small Negative Forecast Errors.

	Analysts	
	Experienced	Inexperienced
% Small Positive Forecast Error	14.33 %	9.40 %
% Small Negative Forecast Error	7.53 %	12.93 %
% Difference	6.80 % **	-3.53 %

This table conducts a comparison between the percentage of the small positive and small negative forecasts errors for both type of analysts. We keep observations within forecast errors of -1% and +1% . General experience is the number of quarters for which the analyst supplied at least one forecast during the first two months of the quarters. We group analysts into Inexperienced and Experienced categories based on their general experience measure. Experienced (Inexperienced) analysts are analysts with general experience higher (lower) than the median. *The Forecast Error (SUE)* is the difference between the actual annual earnings and the analyst forecast estimate, divided by the share price at the beginning of the calendar quarter. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the two-sample test of proportions.

Table 3.3. The Average Market Capitalization per Size Decile of the Eligible Firms Included in the Sample.

	Average Market Cap in millions		
	Firms followed by		
size decile	inexp. analysts	exp. analysts	All Firms
1	61.08	69.06	63.07
2	136.83	142.94	137.02
3	235.91	243.04	235.93
4	384.60	399.49	387.00
5	620.16	633.22	622.31
6	982.07	1007.05	989.04
7	1567.68	1607.23	1588.18
8	2668.99	2781.81	2734.07
9	5476.54	5936.52	5779.36
10	21295.39	33620.50	30889.76

This table reports the average market capitalization in millions per size decile of the eligible firms included in our sample. A firm is eligible to be included in our sample if it has a data entry in both CRSP daily file and I/B/E/S quarterly detail database. It also must be followed by at least four analysts. The data sample is from January 1988 to January 2018. We group analysts into Inexperienced and Experienced categories based on their general experience measure. If the number of experienced analysts exceeds the inexperienced analysts, the firm is considered followed mainly by experienced analysts and vice versa.

Table 3.4. The Average Daily Returns of Firms Followed by Experienced and Inexperienced Analysts.

	Average Daily Returns in %										
	t	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
folowed by inexp. ana.	0.173	0.305	0.341	0.345	0.350	0.415	0.491	0.535	0.606	0.648	0.726
folowed by exp. ana.	0.169	0.315	0.370	0.406	0.475	0.538	0.631	0.715	0.809	0.899	0.976
difference	−0.004	0.010	0.029	0.061	0.125*	0.122*	0.139**	0.180**	0.203**	0.251**	0.249**

This table reports the average returns of firms followed by experienced and inexperienced analysts on the announcement day and the following $1 \cdots 10$ days. The sample period is from January 1988 to January 2018. We group analysts into Inexperienced and Experienced categories based on their general experience measure. Experienced (Inexperienced) analysts are analysts with general experience higher (lower) than the median. If the number of experienced analysts exceeds the inexperienced analysts, the firm is considered followed mainly by experience analysts and vice versa. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 3.5. The Average Daily Returns of Firms Followed by Experienced and Inexperienced Analysts and Unexpected Earnings

		Average Daily Returns in %										
Firms	SUE	t	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
folowed by inexp. ana.	*positive*	.72	1.482	1.601	1.646	1.682	1.769	1.864	1.889	1.987	2.044	2.145
	negative	−.522	−1.293	−1.347	−1.41	−1.456	−1.392	−1.319	−1.252	−1.218	−1.167	−1.117
folowed by exp. ana.	*positive*	.725	1.419	1.551	1.602	1.706	1.813	1.913	2.012	2.126	2.213	2.278
	negative	−.692	−1.467	−1.543	−1.569	−1.563	−1.546	−1.476	−1.422	−1.346	−1.257	−1.196

This table reports the average returns of firms followed by experienced and inexperienced analysts on the announcement day and the following $1 \cdots 10$ days for positive and negative unexpected earnings. We group analysts into Inexperienced and Experienced categories based on their general experience measure. Experienced (Inexperienced) analysts are analysts with general experience higher (lower) than the median. If the number of experienced analysts exceeds the inexperienced analysts, the firm is considered followed mainly by experience analysts and vice versa. The standardized unexpected earnings (SUE) for both types of analysts is the quarterly actual earnings per share (as reported in I/B/E/S) minus the average forecast provided by experienced analysts or inexperienced analysts, scaled by the price at the beginning of the quarter.

Table 3.6. Absolute Value of Unexpected Earnings and Trading VolumE.

Panel A: Firms followed by inexperienced analysts				
	volume		Abs. SUE	
Abs. SUE	Mean	Med	Mean	Med
1 Low	0.902	0.736	0.027	0.026
2	0.964	0.823	0.124	0.122
3	0.987	0.865	0.319	0.315
4 High	1.135	0.996	2.331	1.962
High-Low	0.233***			

Panel B: Firms followed by experienced analysts				
	volume		Abs. SUE	
Abs. SUE	Mean	Med	Mean	Med
1 Low	0.967	0.745	0.028	0.026
2	1.085	0.853	0.123	0.121
3	1.221	1.022	0.315	0.309
4 High	1.458	1.213	2.023	1.589
High-Low	0.491***			

This table reports the absolute value of unexpected earnings and the magnitude of the daily abnormal trading volume for firms followed by experienced analysts (Panel A) and inexperienced analysts (Panel B). The sample period is from January 1988 to January 2018. The standardized unexpected earnings (SUE) for both types of analysts is the quarterly actual earnings per share minus the average forecast provided by experienced analysts or inexperienced analysts, scaled by the price at the beginning of the quarter. The abnormal volume is calculated as the difference between the actual percentage of shares traded on the announcement day and the median non-announcement volume. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 3.7. Daily Trading Volume Within Small, Medium and Big Firms.

Panel A: Firms followed by inexperienced analysts

	volume		Abs. SUE	
size	Mean	Med	Mean	Med
1	1.000	0.750	4.35	3.194
2	1.101	0.850	1.311	1.024
3	0.984	0.793	0.529	0.386
3-1	−0.016			

Panel B: Firms followed by experienced analysts

	volume		Abs. SUE	
size	Mean	Med	Mean	Med
1	0.888	0.708	3.274	2.323
2	0.862	0.940	1.005	0.695
3	1.040	0.851	0.417	0.305
3-1	0.151***			

This table reports the magnitude of the daily abnormal trading volume within small, medium and big firms. Panel A reports the results for firms that are followed mainly by inexperienced analysts and Panel B reports the results for firms that are followed mainly by experienced analysts. The sample period is from January 1988 to January 2018. The standardized unexpected earnings (SUE) for experienced and inexperienced analysts is the quarterly actual earnings per share minus the average forecast provided by experienced analysts or inexperienced analysts, scaled by the price at the beginning of the quarter. The abnormal volume is calculated as the difference between the actual percentage of shares traded on the announcement day and the median non-announcement volume. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 3.8. Daily Trading Volume by Size and Consensus SUE.

		Panel A: Firms followed by inexperienced analysts				**Panel B: Firms followed by experienced analysts**			
		volume		Abs. SUE		volume		Abs. SUE	
size	Abs. SUE	Mean	Med	Mean	Med	Mean	Med	Mean	Med
1	1	0.898	0.885	0.028	0.028	0.878	0.798	0.029	0.029
1	2	0.869	0.863	0.129	0.128	0.994	0.912	0.128	0.127
1	3	0.791	0.764	0.327	0.326	0.961	0.881	0.327	0.326
1	4	1.061	1.009	3.649	3.298	1.281	1.170	3.022	2.752
	4-1	0.163*				0.403***			
2	1	0.900	0.868	0.028	0.028	1.132	1.036	0.030	0.029
2	2	1.041	1.008	0.123	0.123	1.179	1.079	0.123	0.123
2	3	1.045	0.993	0.319	0.318	1.283	1.196	0.315	0.314
2	4	1.028	0.975	1.903	1.804	1.678	1.595	2.102	2.005
	4-1	0.128				0.546***			
3	1	0.785	0.752	0.026	0.026	0.874	0.790	0.027	0.026
3	2	0.838	0.818	0.121	0.120	1.049	0.992	0.121	0.120
3	3	0.937	0.926	0.310	0.308	1.127	1.068	0.308	0.306
3	4	1.079	1.072	1.829	1.802	1.430	1.380	1.650	1.529
	4-1	0.294				0.556***			

This table reports the magnitude of the daily abnormal trading volume by size and consensus SUE. Panel A reports the results for firms that are followed mainly by experienced analysts and Panel B reports the results for firms that are followed mainly by experienced analysts. The sample period is from January 1988 to January 2018. We first rank each type of firm into three groups based on their market capitalization and for each firm size group, we rank firms based on their consensus SUE. The standardized unexpected earnings (SUE) for experienced, inexperienced and all analysts is the quarterly actual earnings per share minus the average forecast provided by experienced analysts or inexperienced analysts, scaled by the price at the beginning of the quarter. The daily abnormal volume is calculated as the difference between the actual percentage of shares traded on the announcement day and the median non-announcement volume. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 3.9. Daily Trading Volume during the 15 Days Period Centered on the Announcement Day.

	Firms followed by inexperienced analysts		Firms followed by experienced analysts	
day	Mean	Median	Mean	Median
-7	0.286	0.186	0.208	0.172
-6	0.192	0.101	0.178	0.082
-5	0.167	0.071	0.144	0.048
-4	0.161	0.068	0.150	0.050
-3	0.174	0.075	0.143	0.043
-2	0.162	0.067	0.128	0.029
-1	0.144	0.053	0.120	0.022
0	0.844	0.671	0.915	0.697
1	1.172	0.981	1.306	1.061
2	0.528	0.397	0.568	0.421
3	0.378	0.262	0.394	0.272
4	0.298	0.195	0.318	0.203
5	0.275	0.17	0.275	0.161
6	0.239	0.142	0.240	0.131
7	0.210	0.011	0.207	0.103

The table reports the daily trading volume for firms followed by experienced analysts and firms followed by inexperienced analysts during the 15 days period centered on the announcement day. The abnormal volume is calculated as the difference between the actual percentage of shares traded on the announcement day and the median non-announcement volume.

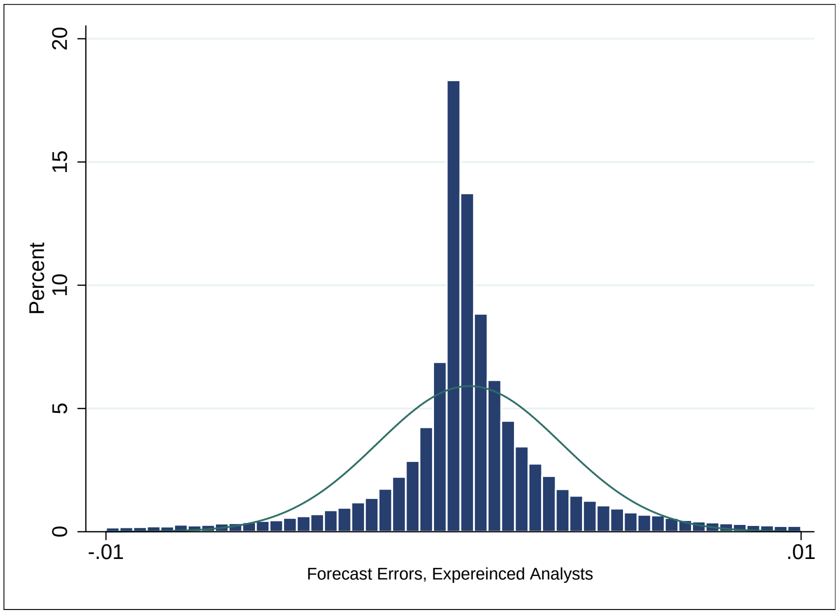
Table 3.10. Daily Trading Volume in the Lowest and Highest Quartile SUE During the 15 Days Period Centered on the Announcement Day.

	Firms followed by inexperienced analysts			Firms followed by experienced analysts		
	Low Abs.SUE	High Abs.SUE	Difference	Low Abs.SUE	High Abs.SUE	Difference
-7	0.297	0.289	0.079***	0.376	0.423	0.134***
-6	0.185	0.176	0.075***	0.260	0.263	0.087***
-5	0.171	0.131	0.050***	0.221	0.215	0.084***
-4	0.146	0.122	0.074***	0.22	0.187	0.065***
-3	0.160	0.105	0.054***	0.214	0.193	0.088***
-2	0.128	0.096	0.073***	0.201	0.168	0.072***
-1	0.123	0.093	0.066***	0.189	0.175	0.082***
0	0.924	1.082	0.083**	1.007	1.211	0.129***
1	1.097	1.147	0.278***	1.375	1.640	0.493***
2	0.486	0.484	0.160***	0.646	0.761	0.277***
3	0.322	0.306	0.121***	0.443	0.542	0.236***
4	0.251	0.244	0.122***	0.373	0.439	0.195***
5	0.229	0.209	0.089***	0.318	0.375	0.166***
6	0.200	0.177	0.081***	0.281	0.345	0.168***
7	0.187	0.168	0.069***	0.256	0.326	0.158***

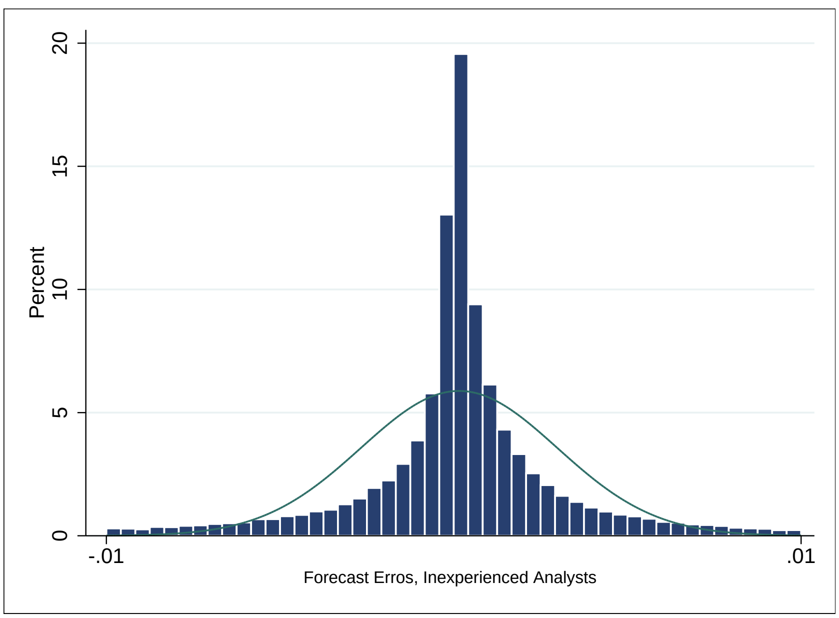
The table reports the daily abnormal trading volume for firms followed by experienced analysts and firms followed by inexperienced analysts in the lowest and highest SUE during the 15 days period centered on the announcement day. The standardized unexpected earnings (SUE) for both types of analysts is the quarterly actual earnings per share minus the average forecast provided by experienced analysts or inexperienced analysts, scaled by the price at the beginning of the quarter. The abnormal volume is calculated as the difference between the actual percentage of shares traded on the announcement day and the median non-announcement volume.

Figure 3.1. The Percentage of Forecast Errors for Observations within Forecast Errors of -1% and +1%.

(a) Experienced Analysts



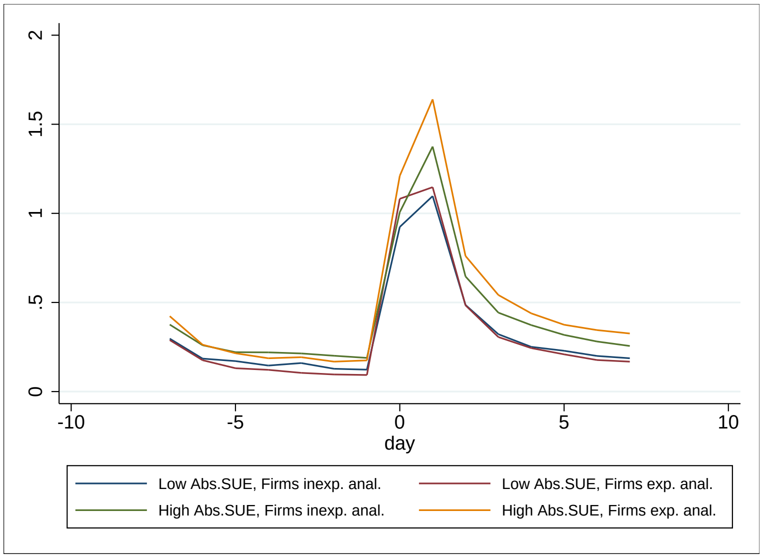
(b) Inexperienced Analysts



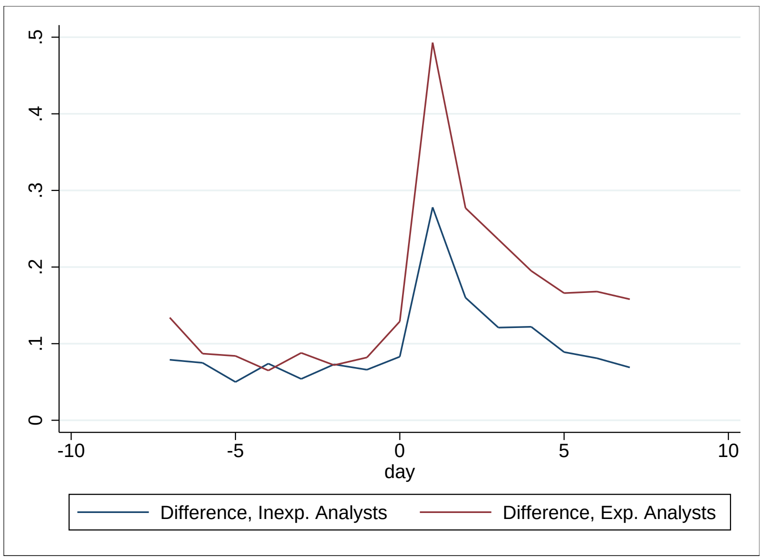
This figure presents the percentage of forecast errors for observations within forecast errors of -1% and +1% for Experienced Analysts (Panel a) and Inexperienced Analysts (Panel b). The data sample is from January 1988 to January 2018. We calculate the standardized unexpected earnings (SUE) for both type of analysts as the quarterly actual earnings per share minus the average forecast provided by experienced analysts or inexperienced analysts, scaled by the price at the beginning of the quarter. We group analysts into Inexperienced and Experienced categories based on their general experience measure. Experienced (Inexperienced) analysts are analysts with general experience higher (lower) than the median.

Figure 3.2. The smallest versus the highest Abs. SUE quartiles trading volumes during the 15 days period centered on the announcement day.

(a) Trading Volume



(b) Difference



This figure plots in Panel (a) the smallest versus the highest Abs. SUE quartiles anormal daily trading volumes for firms followed mainly by experienced analysts and firms followed mainly by inexperienced analysts during the 15 days period centered on the announcement day. The differences in the trading volumes across Abs. SUE quartiles for both firm categories are plotted in Panel (b).

Chapter 4

Dispersion, Short Sale Constraints and Stock Returns

4.1 Introduction

Several studies have documented that in the presence of heterogeneous beliefs, short sale constrained stocks are overpriced and exhibit negative abnormal returns. The contribution of this chapter is to shed light on the high abnormal returns observed in a portfolio formed by unconstrained and low level of opinion divergence stocks. Intuitively, these stocks should be fairly priced as all the information (positive or negative) is incorporated into the prices in the absence of short sale constraints.

In the empirical investigation, I find that a portfolio formed by stocks with low dispersion and low short interest ratio earns significantly higher future returns than a portfolio formed by otherwise similar stocks. I show that such portfolio contains stocks with low total and idiosyncratic risks, low growth, and low leverage. Note that three and four factors models, as well as liquidity factors models, cannot account for these high abnormal returns. Diether et al. (2002) were the first to document empirically, a negative relation between dispersion and returns, which they justify by the Miller (1977) prediction.

In the empirical analysis, the short interest ratio (SIR) is the proxy for short sale constraints, and the coefficient of variation of analyst forecast (CV) is the proxy for the opinion divergence. A low SIR and CV stock is considered unconstrained with a low level of opinion divergence. Sorting the stocks into five groups based on the two proxy variables yields a positive linear relation between SIR, CV, and future returns. A portfolio formed by low SIR and CV stocks outperforms a portfolio formed by high SIR and CV stocks. While the existence of these abnormal returns in the empirical literature (Boehmer, Huszar, and Jordan (2010)) does not seem much controversial, it is much less clear what might be driving it.

The use of the SIR prompts us to look more closely to the market constituents. To do so, I examine the proportion of pessimists and optimists in the different SIR and CV quintiles. I notice that low CV and SIR quintile contains more optimists than pessimists compared to the high CV and SIR quintile. Linking this finding to the high abnormal returns earned by investing into portfolios formed by unconstrained stocks with low opinion divergence, I see that short sellers are informed investors.

The rest of this chapter is organized as follows: The next section describes the data and the proxies used. It also presents a brief overview of the literature related to dispersion and short sale constraints proxies. Section 3 illustrates the procedure of forming portfolios based on analysts' forecasts dispersion and short sale constraints. It also presents the initial results. Section 4 analyzes the idiosyncratic and total risks in the different portfolios formed. Section 5 explores the abnormal returns in the three and four factors models, as well as the liquidity factors models and presents the results of the regressions when controlling for some variables known in the literature to explain the risk premium. Section 6 evaluates the firm characteristics based on dispersion and short sale constraints proxies. The last section of this chapter concludes.

4.2 Data Description

4.2.1 Dispersion of Opinion

In this section, I turn my attention to papers that investigate the effect of heterogeneous beliefs on stock prices. I first cite Diether et al. (2002). The authors use the I/B/E/S coefficient of variation, defined as the ratio of the standard deviation in analysts' forecasts to the absolute mean of analyst forecasts, and suggest that stocks with high disagreement earn low future returns. Using the same proxy of dispersion, Sadka and Scherbina (2007) demonstrate that the overpricing of high disagreement stocks is explained by the low liquidity characteristic of these particular stocks. Yu (2011) shows that market disagreement is negatively related to expost expected future returns using the IBES coefficient of variation. Qu et al. (2003) also use the standard deviation of the current fiscal year earnings per share forecasts, scaled by stock price, as their base measure of forecast dispersion and find a positive relationship between disagreement and returns. Note that the majority of the previous work focuses mainly on examining the return behavior in the high dispersion side but do not consider explaining the high abnormal returns associated with low dispersion.

To proxy for the dispersion of opinion, I use the coefficient of variation of analyst forecast (CV). Following Diether et al. (2002), I measure the CV by dividing the standard deviation of analyst earnings per share for the current fiscal year by the absolute value of the mean earnings per share forecast. I use I/B/E/S summary history data set to calculate the CV. To see the behavior of the firm level dispersion series, I plot the dispersion series for ten firms in figure 4.1.

4.2.2 Short Sale Constraints

Figlewski (1981) is among the first authors who investigate the effect of the short sale constraints on stock prices. He uses the short sale interest ratio as a proxy of short sale constraints and finds that unconstrained stocks display significant positive abnormal returns and constrained stocks display insignificant negative abnormal returns. Using monthly short interest data in the universe of the NASDAQ firms, Desai, Ramesh, Thiagarajan, and Balachandran (2002) find high significant negative abnormal returns for high short interest stocks. Chen et al. (2002) show that constrained stocks subsequently underperform the unconstrained ones. In their analysis, a decline in the breadth of ownership, defined by the ratio of mutual funds that hold a long position into the stock to the total number of mutual funds in the sample for a specific quarter, leads to short sale constraints becoming more tightly binding. Asquith, Pathak, and Ritter (2005) confirm that constrained stocks underperform the market. They define constrained stocks by a high short interest ratio (a proxy of demand) and low institutional ownership (a proxy of supply). Chang, Cheng, and Yu (2007) find evidence supporting the Miller (1977) intuition using Hong Kong stock market data. Diether, Lee, and Werner (2008) study the short sale activity at a higher frequency and find that high returns periods are followed by an increase in the short sale activity leading to negative abnormal subsequent returns. Boehmer et al. (2010) use Figlewski (1981) proxy of short sale constraints and find evidence that unconstrained stocks outperform the constrained stocks. More recently Rapach, Ringgenberg, and Zhou (2015) find that short interest, when aggregated across firms is a statistically and economically significant predictor of future market excess returns.

To proxy for the short sale constraints, I use the relative short interest ratio (SIR). The SIR is estimated by dividing the short interest by the total share outstanding. Short sale constrained stocks are socks with the highest SIR. The intuition is when stocks are heavily shorted, it will be harder for the investors to short them. Short interest data is obtained from COMPUSTAT. This data is collected monthly for the transaction settling by the 15th of each month. It is worth noting that a better proxy for short sale constraints should be used. To investigate the behavior of the individual SIR series, I plot the SIR time series for ten firms in Figure 4.2.

4.2.3 Data

The monthly returns and stock characteristics (volume, shares outstanding, price...) are from CRSP. I include stocks listed in New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and The Nasdaq Stock Market with share code 10 or 11 (common stocks). In order to ensure that the illiquid stocks are not considered in the analysis, I exclude penny stocks (price $<$ \$5).

Note that to construct the short selling constraint and dispersion proxies and to access the stock returns, I need to merge three different databases. To do so, I merge COMPUSTAT data to CRSP data using the 8-digit CUSIP code, and I merge IBES data to CRSP data using NCUSIP code in IBES and the CUSIP code in CRSP. I keep a stock in the data set if it has an entry in CRSP, COMPUSTAT, and IBES databases. This will reduce the number of observations in the sample significantly. The sample obtained when merging the three databases is mainly composed of medium and large firms. This problem was also mentioned by Diether et al. (2002) and Hong et al. (2000). Data are measured at monthly frequency unless otherwise specified. This analysis covers a period of 408 months, starting from January 1985 to December 2018.

4.3 Portfolio Performance

Each month, stocks are sorted based on market capitalization into three groups. Each subgroup is first sorted by dispersion then by short interest ratio. Table 4.1 displays the monthly average returns, computed as the equal-weighted average of returns, in the different 27 portfolios. Results show that low and high SIR and CV portfolios earn the highest and the lowest returns, respectively. In particular, the low SIR and low CV portfolio earns 1.59 % for small firms, 1.34 % for medium firms, and 1.15 % for large firms. Moreover, the high SIR and CV portfolio earns 1.21% for small firms, 0.868 % for medium firms, and 0.952 % for large firms.

In the following sections, I will focus only on the diagonal portfolios. That is, a stock A is considered in the portfolio i if, for the same month, A is in quintile i based on SIR and in quintile i based on CV where $i : 1, \cdots, 5$. After forming the portfolios, stocks are held for a horizon of one month. Table 4.2 reports the results for low, medium, and high market capitalization. The last column contains the results for the total sample.

All columns in Table 4.2 show that there is a negative relation between the returns and the two proxies combined. Unconstrained Stocks with low dispersion exhibit the highest returns. This is counter-intuitive, as these stocks should incorporate all the information available in the market, positive and negative. Thus, these stocks should be fairly priced. Notice that the Miller (1977) hypothesis, stating that the divergence of investor's opinion in the presence of short sale constraints leads to overvaluation and lower returns, is verified in the highest quintile but cannot explain the high returns observed in the lowest quintile.

4.3.1 Momentum Sorting

In this section, I first sort the stocks into three groups based on the past returns from $t-12$ to $t-2$. Then within each momentum group, I sort stocks into three sub-groups based on CV and SIR. Same as the previous section, I keep the intersection between the ranking based on CV and SIR. The results in table 4.3 show that the returns are again higher in the lowest SIR and CV group. Therefore, the returns are not driven by the momentum effect described in Jegadeesh and Titman (1993).

4.4 Portfolio Risk and Return

Now, I investigate the relationship between risk and return. Total and idiosyncratic risks are sorted based on CV and SIR similarly to the returns in the previous section. The goal is to observe the level of risk in the low and high CV and SIR quintiles.

To compute the total monthly equity volatility, I use daily CRSP returns ranging from 1985 to 2017. Following Fu (2009) and Ang, Hodrick, Xing, and Zhang (2009), I compute the idiosyncratic volatility of the stock i as the sum of squared residuals of the regression (1). I obtain the Fama-French three factors data and the momentum from the WRDS database.

$$r_{it} = \alpha_i + b_i \times R_t^{MKT} + s_i \times SMB_t + h_i \times HML_t + u_i \times UMD_t + \epsilon_i, \qquad (4.1)$$

where r_{it} is the individual stock excess return, R_t^{MKT} is the market excess return at t, SMB_t is the average return on the three small portfolios minus the average return on the three big portfolios, HML_t is the average return on the two value portfolios minus the average return on the two growth portfolios and UMD_t is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

The results, in table 4.4, display a negative relationship between risk and returns. Despite the low firm-specific risk and total risk, low CV and SIR stocks outperform the high CV and SIR stocks. The high returns obtained are not driven by the large firm-specific risk in the portfolio. These results are consistent with the idiosyncratic volatility puzzle (Ang et al., 2009), where stocks with high idiosyncratic volatility earn low average returns.

We might think that the lowest CV quintile is composed of investors that agree (low dispersion) on the future performance of the stock (good or bad). The low level of the short interest (low SIR) indicates that stocks are mainly held long. Therefore, investors are mainly optimistic.

The highest CV and SIR quintiles present the opposite intuition. Investors disagree on the performance of the firm (high CV). The market contains a large portion of pessimist investors (high SIR) who can short the stocks at some extend. At least, investors with a strong negative signal act first and short the stock. Other investors with relatively less negative signals will not be able to short the stock since it becomes constrained. We might think of short sellers as informed traders rather than speculators. They can differentiate between low and high risk stocks and choose their position accordingly.

In the argument above, the low level of short interest implies a lower proportion of pessimistic investors trading the stock compared to the proportion of optimistic investors in the market. Similarly, a high level of short interest indicates that the market contains more pessimist investors that are willing to short sale the stock.

To test this intuition, I use detail history IBES data from 1985 to 2018. I calculate the month end earnings forecasts averages from the individual earnings forecasts in the detail history file using the same approach described in Diether et al. (2002). Then, I compare the monthly averages obtained to the individual estimates of earnings per share. If the estimate is higher than the mean, the analyst is considered optimist, and if the estimate is lower than the mean, the analyst is considered pessimist. Then, for every firm, I create the percentage of the pessimists (optimists) every month, defined by the ratio of the number of pessimists (optimists) to the total number of analysts following the firm. The percentages of the pessimists and optimists are then sorted based on CV and SIR separately. Finally, I create an average of the percentages across quintiles. Table 4.5 reports the sorting relative to the percentage of pessimists.

Results in table 4.5 justify our intuition. Low SIR and CV quintile contains the lowest proportion of pessimists. Short sellers do not have strong negative information to short sale the stocks which turn out to be true as the stock moves up and exhibit a higher return. In the opposite side, high SIR and CV quintile contains the largest proportion of pessimists. Short sellers have enough negative information to short the stock (if possible). The results hold for low, medium, and high market capitalization in the stock universe.

4.5 Regression Tests

4.5.1 Three and Four Factors Models Regressions

This section tests the abnormal returns using the three and four factors models (Fama and French (1993) and Carhart (1997)) as follow :

$$R_{it} - rf_t = \alpha_i + b_i \left(R_{mt} - rf_t \right) + s_i SMB_t + h_i HML_t + m_i UMD_t + \epsilon_i \qquad (4.2)$$

Fama-French three factors and the momentum factor data are obtained from the WRDS database. The intercept α captures the average annual abnormal performance. The three factors model captures the market, value and size premiums. Fama and French (1993) model states that value, and small stocks outperform growth and large stocks. The Carhart (1997) fourth factor captures the premium on winners minus losers.

Results in table 4.6 show that the portfolios formed by low CV and SIR stocks display significant monthly positive abnormal returns of 1.19 and 1.18 percent when considering the three factors model and the four factors model, respectively.

4.5.2 Liquidity Risk Factor

I also test for the liquidity risk in the portfolio formed on CV and SIR quintiles as follow:

$$R_{it}-rf_t = \alpha_i + b_i \times (R_{mt} - rf_t) + s_i \times SMB_t + h_i \times HML_t + m_i \times UMD_t + l_i \times LIQ_t + \epsilon_i \quad (4.3)$$

I refer to two well-known measures of liquidity. The first measure $LIQ_{P\dot{S}}$ is the aggregate liquidity in the market developed by Pastor and Stambaugh (2003). The authors find evidence that the expected stock returns are positively related to the sensitivities of returns to the fluctuations in aggregate liquidity. The second measure is developed by Sadka (2006). The author decomposes the liquidity into variable and fixed components ($LIQ_{S.var}$; $LIQ_{S.fix}$). He shows that the variable component can explain the expected momentum portfolio returns. Table 4.6 shows that including the liquidity factors to the four factors regression does not affect the results. I still obtain positive significant abnormal returns of 1.32 and 0.97 percent in portfolio formed by lightly shorted stocks with low dispersion using Pastor and Stambaugh (2003) and Sadka (2006) liquidity measures, respectively.

I also considered creating a firm level liquidity measure based on Pastor and Stambaugh (2003) methodology. I omitted the less liquid stocks from the sample, and I performed the usual sorting exercise. The results obtained are supporting the fact that liquidity does not explain the high returns obtained in the low CV and SIR quintiles.

Several research papers relate high returns on portfolio formed by low volume stocks to low liquidity. Their argument is based on the fact that low volume stocks are less liquid and therefore, command higher expected returns. In order to verify that the returns on the lightly shorted stocks with low dispersion are not driven by low liquidity, I first sort the stocks into three groups based on their last month turnover, defined as the ratio of the number of shares traded on a month to the number of share outstanding. Each group is then sorted into five subgroups based on CV and SIR.

The results on table 4.7 show that the liquidity is, again, not the explanation of the high returns. The sorting exercise confirms the negative relation between returns and the two proxies used in the low, medium, and high turnover groups.

4.6 Alternative Hypotheses

In this section, I control for various variables known in the literature to affect the equity premium. These variables include the level of consumption compared to wealth (CAY), the default yield spread, inflation, and VIX. First, I add the control variables one by one, then I include all the variables in the regression as follow:

$$r_{t+1} = \alpha + \beta_1 \times \text{CAY}_t + \beta_2 \times \text{Default spread}_t + \beta_3 \times \text{Inflation}_t + \beta_4 \times \text{VIX}_t + \epsilon_t \tag{4.4}$$

Quarterly data on CAY are obtained from Martin Lettau's Web site. The default yield spread measures the spread between BAA and AAA-rated corporate bond yields. The monthly data on inflation and the default spread is obtained from the Web site of Amit Goyal. And finally, the Volatility Index (VIX) is obtained from the CBOE database in WRDS.

Table 4.8 lists the results of the regressions. Low CV and SIR quintile still displays high intercept α compared to the high CV and SIR quintile. The results on the low CV and SIR quintile are only significant for the aggregate consumption-wealth ratio CAY ($\alpha = 1.18\%$), the default spread ($\alpha = 0.97\%$) and inflation ($\alpha = 1.15\%$). The highest CV and SIR quintile presents insignificant low abnormal returns.

4.7 Firm Characteristics

This section reports some firm characteristics depending on its ranking based on CV and SIR. As discussed above, I see short sellers as informed investors that can differentiate between high and low performing firms. I hypothesize that the high CV and SIR quintile will contain the lowest growth and the most leveraged firms.

To test this hypothesis, I will sort the leverage ratio and capital growth based on CV and SIR.

4.7.1 Leverage

I define leverage as the ratio of total debt to total asset where the total asset is measured by the sum of the two sources of financing. Data are obtained from COMPUSTAT from January 1985 to December 2018. Concentrating on leverage to investigate the performance of the firm is justified by several studies in the literature. I cite for example Myers (1977) and Lang, Ofek, and Stulz (1996) who argue that leverage could negatively affect firm growth.

The sort exercise of the leverage ratio on CV and SIR leads to a positive linear relation between leverage and the two sorting variables, as shown in table 4.9. As the levels of dispersion and short interest ratio increase the leverage ratio increases. High CV and SIR quintile presents the highest leverage ratio of 48.23 percent compared to the low CV and SIR quintile, where the leverage ratio is 42.74 percent.

4.7.2 Growth

This section concentrates on firm growth. The growth measure used is the investment growth rate , which is the ratio of the capital expenditure at month t minus the capital expenditure at month $t-1$ to the capital expenditure at month $t-1$. In order to obtain monthly observations on investment, I use interpolated values. Investment growth rates are sorted into five groups based on CV and SIR. Equally-weighted averages are then computed, as shown in table 4.10. The results are counter-intuitive, low (high) CV and SIR quintile presents the lowest (highest) growth rates.

4.8 Conclusion

This chapter discusses the empirical relation between stock returns, dispersion, and short sale constraints. Unconstrained and low level of opinion divergence stocks, tend to generate high returns, low idiosyncratic and total risks, display low growth rates, and low leverage ratios. Three and four factors models, as well as liquidity factors, cannot account for these high abnormal returns. The negative correlation between disagreement and expected returns is treated mainly using divergence of opinion models. It is important to note that Diether et al. (2002)'s results do not hold when I include observations until December 2018. The empirical analysis also provides some insight into market constituents in the different CV and SIR samples. Low CV and SIR quintiles contain more optimists than pessimists. Short sellers in this situation might be treated as informed traders who use their informed signals to short sale the stock.

Table 4.1. Mean Portfolio Returns by Market Capitalization, Short Interest Ratio and Dispersion.

	Mean Returns %								
	Low mcap						High mcap		
CV	Low SIR	Med SIR	High SIR	Low SIR	Med SIR	High SIR	Low SIR	Med SIR	High SIR
1	1.59	1.443	1.258	1.34	1.266	0.968	1.153	1.085	1.07
2	1.594	1.434	1.266	1.234	1.135	0.889	1.183	.958	.861
3	1.589	1.481	1.21	1.163	1.205	0.868	1.020	.993	0.952

Each month, stocks are sorted into three sub-sample based on their market capitalization. Each sub-sample is first sorted into 3 groups based on CV. Then each sub-sample is sorted by SIR into 3 groups. Stocks with a price less than five dollars are omitted. The portfolio returns are equally-weighted and stocks are held for a horizon of one month. The returns presented are monthly. The sample covers the time period from January 1985 to December 2018.

Table 4.2. Mean Portfolio Returns by Market Capitalization and Short Interest Ratio and Dispersion Intersection.

	Mean Returns %			
CV & SIR	Low mcap	Med mcap	High mcap	Total
1	1.544	1.493	1.201	1.388
2	1.436	1.141	1.107	1.227
3	1.351	1.073	1.010	1.168
4	1.229	1.040	0.883	1.056
5	1.019	0.945	0.848	0.927
1-5	0.525 **	0.548 **	0.352 *	0.462 **
All Sample	1.323	1.130	0.996	

Each month, stocks are sorted into three sub-sample based on their market capitalization. Each sub-sample is sorted into 5 groups based on both the SIR and CV. The stock is kept into our sample if it has the same rank based on the two proxies. Stocks with a price less than five dollars are omitted. The portfolio returns are equally-weighted and stocks are held for a horizon of one month. The returns presented are monthly. The sample covers the time period from January 1985 to December 2018. (*), (**) and (***) are the 10%, 5% and 1% significance levels using the paired-samples t-test.

Table 4.3. Mean Portfolio Returns by Momentum, Short Interest Ratio and Dispersion.

	Mean Returns %		
CV & SIR	Losers		Winners
1	1.184	1.212	1.483
2	0.953	1.129	1.237
3	0.081	0.737	1.097
1-3	1.103 ***	0.474 ***	0.387 **

Each month, stocks are sorted into three samples based on the past returns from $t-12$ to $t-2$. Each sample is sorted into 3 sub-groups based on both the SIR and CV separately. The stock is kept into our sample if it has the same rank based on the two proxies. Stocks with a price less than five dollars are omitted. The portfolio returns are equally-weighted and stocks are held for a horizon of one month. The sample covers the time period from January 1985 to December 2018. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 4.4. Monthly Mean Portfolio Idiosyncratic and Total Risks Sorted by Short Interest Ratio and Dispersion.

Panel A	Mean Idiosyncratic Risk %			
CV & SIR	Low mcap	Med mcap	High mcap	Total
1	25.74	20.74	16.79	20.98
2	26.86	21.97	17.66	22.18
3	30.35	23.81	19.08	24.44
4	35.23	27.96	22.09	28.48
5	41.53	35.05	28.9	34.96
5-1	15.79 ***	14.30 ***	12.10 **	13.98 ***
All Sample	32.12	26.28	21.35	

Panel B	Mean Total Risk %			
CV & SIR	Low mcap	Med mcap	High mcap	Total
1	32.29	28.78	24.19	28.29
2	35.44	30.63	25.73	30.61
3	39.89	33.21	27.64	33.58
4	45.83	38.25	31.68	38.65
5	53.57	47.17	40.39	46.83
5-1	21.28 ***	18.39***	16.20 **	18.54 ***
All Sample	41.58	36.06	30.49	

The table reports mean portfolio idiosyncratic and total risks sorted by short interest ratio and dispersion. The annualized idiosyncratic volatility is estimated by regressing the excess daily returns of each individual stock on the Fama-French three factors and the momentum factor: R^{MKT}, SMB, HML and UMD. The annualized idiosyncratic volatility is the standard deviation of the regression residuals times $\sqrt{252}$. The annualized total volatility is estimated using daily returns obtained form CRSP. Each month, we sort the stocks into three groups based on the market capitalization. Each group is again sorted into 5 sub-groups based on the CV and SIR separately. The stock is kept into our sample if it has the same rank based on the two proxies. The average portfolio idiosyncratic and total risks are equally-weighted. The values presented are annualized. The sample covers the time period from January 1985 to December 2018. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 4.5. Monthly Mean Proportion of Pessimists across Short Interest Ratio and Dispersion Quintiles.

	Mean Percentage of the Pessimist %			
CV & SIR	Low mcap	Med mcap	High mcap	Total
1	48.41	48.13	48.44	48.37
2	50.00	49.22	49.32	49.45
3	50.24	50.71	49.75	50.23
4	52.31	51.89	50.64	51.53
5	53.05	53.47	52.13	52.89
5-1	4.56 ***	5.32 ***	3.65 **	4.51 ***
All Sample	50.79	50.69	50.08	

The table reports the monthly mean proportion of pessimists across short interest ratio and dispersion quintiles. Each month, we create the analysts' forecasts averages using the IBES detail history file. By comparing each forecast to the mean, we differentiate between pessimist and optimists. The percentages of pessimists and optimists are defined by the ratio of pessimists (optimists) to the total number of analysts following the firm. For every stock, the monthly percentage of the pessimists following the stock is sorted into three sub-sample based on the stock market capitalization. Each sub-sample is sorted into 5 groups based on both the SIR and CV. The stock is kept into our sample if it has the same rank based on the two proxies. Stocks with a price less than five dollars are omitted. We form equally-weighted percentages across the quintiles one to five. The sample covers the time period from January 1985 to December 2018. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 4.6. Regressions on the Fama-French Three Factors, Momentum factor and Liquidity Factors

	(1)					(2)				
	PF1	PF2	PF3	PF4	PF5	PF1	PF2	PF3	PF4	PF5
Constant	1.19***	1.05***	1.01***	1.04**	0.89*	1.18***	1.06***	1.04***	1.10***	0.89*
	(5.32)	(4.12)	(3.52)	(3.30)	(2.25)	(5.23)	(4.05)	(3.54)	(3.45)	(2.25)
R^{MKT}_t	-0.027	-0.080	-0.12	-0.16*	-0.14	-0.025	-0.084	-0.12	-0.18*	-0.14
	(-0.59)	(-1.43)	(-1.69)	(-2.21)	(-1.53)	(-0.51)	(-1.41)	(-1.74)	(-2.39)	(-1.49)
SML	-0.048	-0.074	-0.040	-0.021	-0.0041	-0.049	-0.074	-0.039	-0.017	-0.0040
	(-0.63)	(-1.03)	(-0.52)	(-0.23)	(-0.04)	(-0.64)	(-1.00)	(-0.49)	(-0.19)	(-0.04)
HML	0.0050	-0.045	-0.056	-0.037	-0.16	0.0086	-0.050	-0.069	-0.064	-0.16
	(0.06)	(-0.47)	(-0.48)	(-0.28)	(-1.01)	(0.11)	(-0.52)	(-0.57)	(-0.48)	(-0.97)
UMD						0.0099	-0.013	-0.034	-0.076	-0.0017
						(0.22)	(-0.25)	(-0.64)	(-1.14)	(-0.02)
Observations	396	396	396	396	396	396	396	396	396	396

	(3)					(4)				
	PF1	PF2	PF3	PF4	PF5	PF1	PF2	PF3	PF4	PF5
Constant	1.32***	1.20***	1.18***	1.26***	0.98**	0.97***	0.72*	0.66*	0.66	0.35
	(6.06)	(4.87)	(4.39)	(4.22)	(2.62)	(3.62)	(2.45)	(2.06)	(1.85)	(0.81)
R^{MKT}_t	-0.035	-0.093	-0.13	-0.19*	-0.15	-0.038	-0.056	-0.079	-0.17	-0.15
	(-0.69)	(-1.54)	(-1.89)	(-2.52)	(-1.58)	(-0.44)	(-0.57)	(-0.76)	(-1.51)	(-1.05)
SML	-0.051	-0.075	-0.041	-0.019	-0.0052	-0.068	-0.066	-0.046	-0.039	-0.035
	(-0.69)	(-1.04)	(-0.52)	(-0.21)	(-0.05)	(-0.67)	(-0.65)	(-0.41)	(-0.32)	(-0.25)
HML	0.014	-0.044	-0.063	-0.058	-0.16	0.021	-0.011	0.022	0.0054	-0.098
	(0.18)	(-0.46)	(-0.52)	(-0.43)	(-0.94)	(0.18)	(-0.09)	(0.16)	(0.04)	(-0.52)
UMD	0.010	-0.012	-0.034	-0.076	-0.0013	0.053	0.032	0.020	-0.012	0.096
	(0.23)	(-0.24)	(-0.62)	(-1.12)	(-0.02)	(0.81)	(0.50)	(0.29)	(-0.14)	(0.94)
$LIQ_{P,S}$	0.065*	0.061	0.064	0.070	0.043					
	(2.15)	(1.40)	(1.41)	(1.37)	(0.65)					
$LIQ_{S,fix}$						1.00	-0.93	-0.49	-0.38	0.75
						(0.42)	(-0.38)	(-0.19)	(-0.13)	(0.23)
$LIQ_{S,var}$						0.31	0.43	0.58	0.52	0.38
						(0.31)	(0.40)	(0.49)	(0.42)	(0.33)
Observations	396	396	396	396	396	288	288	288	288	288

This table reports the results of the following regressions:

$$r_{it} = \alpha_i + b_i \times R_t^{MKT} + s_i \times SMB_t + h_i \times HML_t + m_i \times UMD_t + l_i \times LIQ_t + \epsilon_i$$

for the five groups formed by sorting the stocks into five quintiles based on CV and SIR. Newey and West (1987) corrections for heteroskedasticity and autocorrelation are applied. The intercepts presented are annualized. The sample covers the time period from January 1985 to December 2018. Stocks with a price less than five dollars are omitted. We obtain the Fama-French three factors, momentum factor and liquidity factor data from the WRDS database. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.7. Mean Portfolio Returns by Turnover, Short Interest Ratio and Dispersion.

	Mean Returns %		
CV & SIR	Low turnover	Med turnover	High turnover
1	1.29	1.44	1.5
2	1.10	1.30	1.04
3	1.08	.96	1.01
4	1.10	1.11	0.88
5	.72	1.15	1.01
1-5	0.578 **	0.290	0.492 *
All Sample	1.06	1.19	1.08

The table reports the mean portfolio returns by turnover, short interest ratio and dispersion. Each month, stocks are sorted into three sub-sample based on their last month turnover. Each sub-sample is sorted into 5 groups based on both the SIR and CV. The stock is kept into our sample if it has the same rank based on the two proxies. Stocks with a price less than five dollars are omitted. Turnover is defined by the ratio of the monthly volume by the share outstanding. The portfolio returns are equally-weighted and stocks are held for a horizon of one month. The sample covers the time period from January 1985 to December 2018. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 4.8. Alternative Hypothesis.

	$\alpha\%$				
	PF1	PF2	PF3	PF4	PF5
CAY	1.18***	1.02***	0.94***	0.97***	0.80*
	(5.89)	(4.64)	(3.93)	(3.48)	(2.26)
Default Spread	0.97***	0.77**	0.71*	0.68*	0.52
	(3.85)	(2.79)	(2.36)	(2.02)	(1.28)
Inflation	1.15***	1.07***	0.95**	1.05**	0.98*
	(4.35)	(3.50)	(2.68)	(2.80)	(2.16)
VIX	1.21	1.02	0.89	0.54	-0.30
	(1.90)	(1.22)	(0.81)	(0.49)	(-0.22)
All	0.69	0.60	0.42	0.16	-0.57
	(1.05)	(0.67)	(0.38)	(0.14)	(-0.40)

The table reports the results of the following regressions:

$$r_{t+1} = \alpha + \beta_1 \times \text{CAY}_t + \beta_2 \times \text{Default spread}_t + \beta_3 \times \text{Inflation}_t + \beta_4 \times \text{VIX}_t + \epsilon_t$$

for the five groups formed by sorting the stocks into five quintiles based on CV and SIR, where r_{t+1} is the return in excess of the risk-free rate for a one month holding period. The first four columns present the results of the regressions where we add the control variables one by one while the last column displays the results of the regression where we add all of the control variables.
The quarterly observations of the aggregate consumption wealth ratio CAY are obtained from Martin Lettau's Web site, we convert the series to monthly data using the last available quarterly value. The other variables are measured monthly. The default spread data is obtained from Federal Reserve Economic data. Inflation is obtained form the Goyal's Web site. And the Volatility Index (VIX) is obtained form the CBOE database in WRDS. Newey and West (1987) corrections for heteroskedasticity and autocorrelation are applied. All control variables are from January 1985 to December 2017 except the Volatility Index VIX where the data starts from January 1990 to January 2011. Stocks with a price less than five dollars are omitted. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.9. The Leverage per Dispersion and Short Interest Quintile Intersection.

	Portfolio					
	1	2	3	4	5	5-1
Average Leverage %	42.74	42.84	43.26	43.28	48.23	5.49 **
Number of observation per month	81	71	65	66	94	

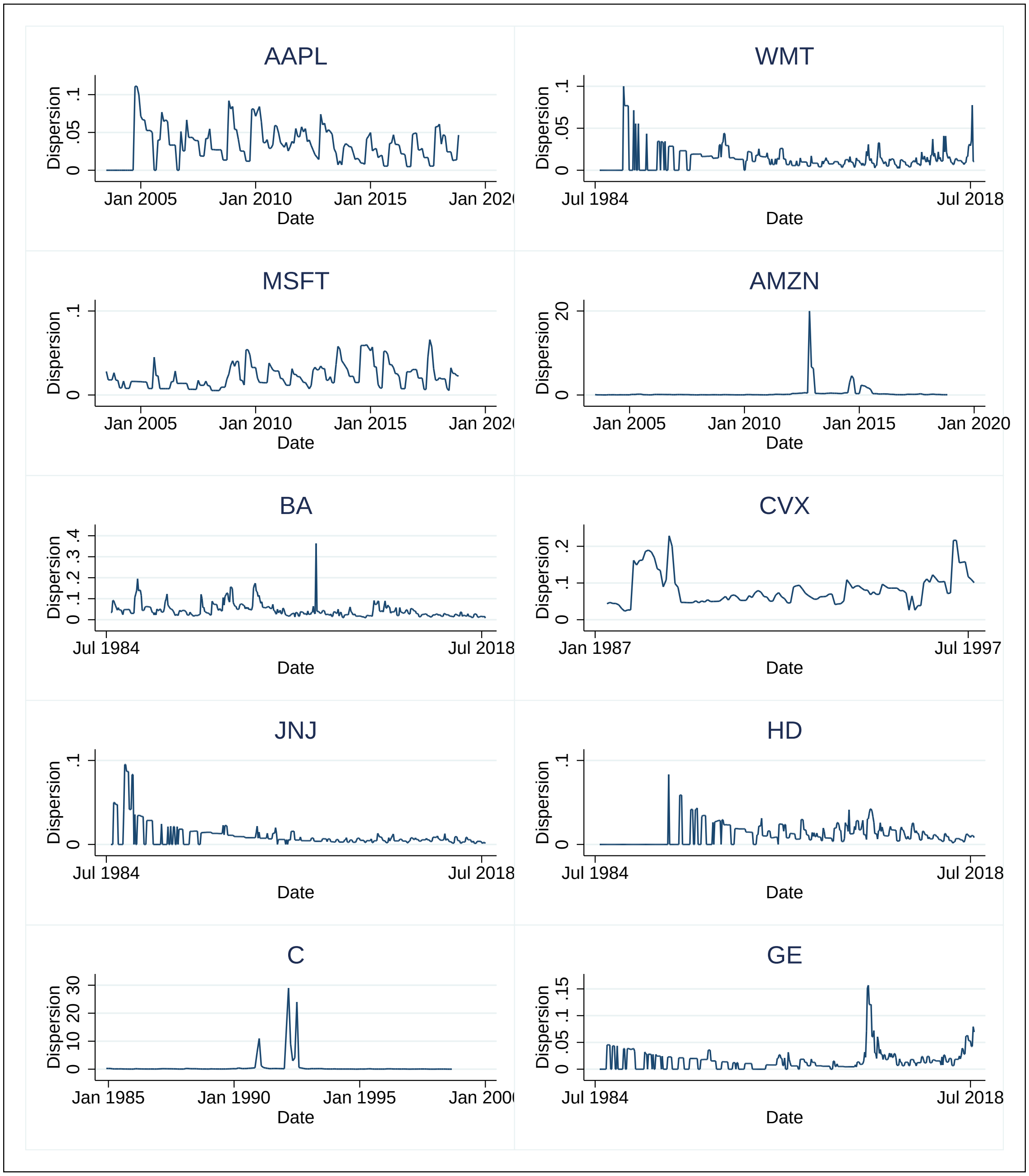
The table reports the leverage ratio by dispersion and short interest ratio. Each month, the leverage ratio defined by the ratio of total debt by total asset, is sorted into 5 groups based on both the SIR and CV. we keep the observation into our sample if it has the same rank based on the two proxies.
Quarterly data is obtained form COMPUSTAT and converted into monthly data using the last available observation. Firms with stock price less than five dollars are omitted. The portfolio leverage ratio averages per quintile one to five is calculated using equal weights. The sample covers the time period from January 1985 to December 2018. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Table 4.10. The Growth by Short Interest Ratio and Dispersion.

	Portfolio					
	1	2	3	4	5	5-1
Average Investment Growth %	3.72	4.35	4.03	4.70	5.20	1.48 *
Number of observation per month	63	55	50	51	71	

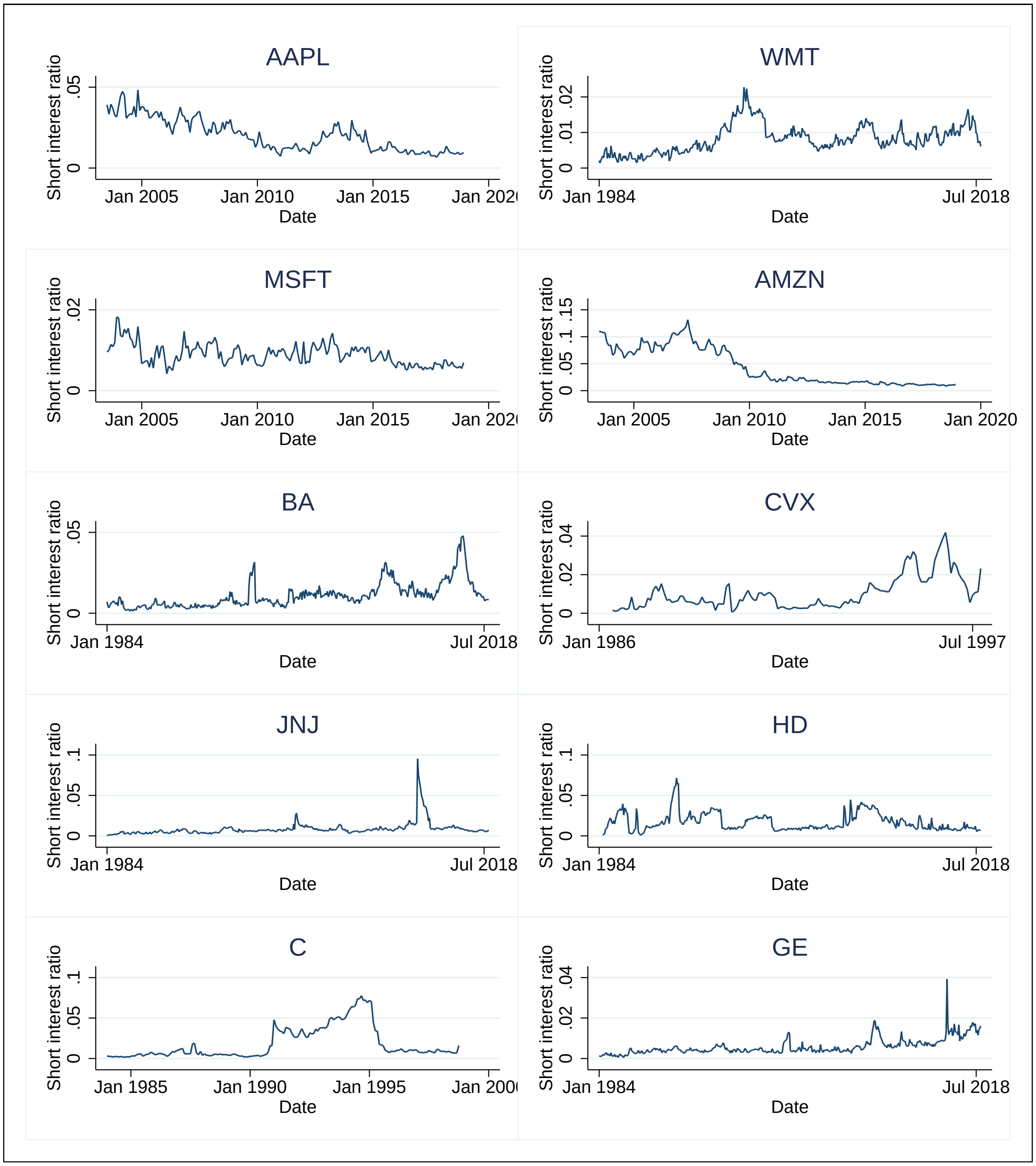
We define the investment growth rate as $\frac{capx_t - capx_{t-1}}{capx_{t-1}}$. The quarterly capital expenditure CAPX are obtained form COMPUSTAT from 1985 to 2018 . To obtain monthly observations on Investment, we use interpolated values. Each month, the investment growth rate, is sorted into 5 groups based on both the SIR and CV. we keep the observation into our sample if it has the same rank based on the two proxies. The investment growth rate average is equally-weighted. Stock price less than five dollars are omitted. (*), (**) and (***) denotes the significance at 10 %, 5 % and 1 % using the paired-samples t-test.

Figure 4.1. Dispersion Series for 10 Different Firms.



This figure plots in the dispersion series for 10 different firms (AAPL, WMT, MSFT, AMZN, BA, CVX, JNJ, HD, C, GE). We measure the CV by dividing standard deviation of analyst earnings per share for the current fiscal year by the absolute value of the mean earnings per share forecast. We use IBES summary history data set to calculate the CV. The sample covers the time period from January 1985 to December 2018.

Figure 4.2. Short Interest Ratio Series for 10 Different Firms.



This figure plots in the SIR series for 10 different firms (AAPL, WMT, MSFT, AMZN, BA, CVX, JNJ, HD, C, GE). The SIR is estimated by dividing the short interest by the total share outstanding. Short interest data is obtained from COMPUSTAT. These data is collected monthly for the transaction settling by the 15th of each month. The sample covers the time period from January 1985 to December 2018.

Chapter 5

Conclusion

This thesis explores how dispersion in analyst's beliefs affects security prices and returns, investigates how analysts experience creates price reaction and discusses the empirical relation between stock returns, dispersion, and short sale constraints.

The first chapter answers the following question: when is the price of dispersion risk positive? We show that aggregate dispersion effect on security's returns varies across different periods of time. Contrary to previous studies, we look at the price of dispersion risk at different sub-samples: full sample, low, medium and high dispersion months. We find, empirically, that the price of dispersion risk is significantly positive in high dispersion months and significantly negative in low dispersion months. The price of dispersion risk is insignificant and close to zero using the full sample and medium dispersion months. Also, the magnitude of the price of dispersion risk is more pronounced in high dispersion months compared to low dispersion months.

We construct a general equilibrium model in which analysts of different types have heterogeneous beliefs and provide different forecasts of a macroeconomic factor (aggregate earnings growth). The consumer does not trust either analyst fully, and dynamically adjusts the weight given to each analyst, given the history of their past forecast performance. A crucial part of the model's mechanism is that the market weights assigned to lower cash flow beta assets increases in periods of higher dispersion, leading to a large loading on the dispersion risk factor. We provide support for such a flight-to-safety phenomenon in the data.

The second chapter focuses on the differences among analysts based on their general experience measure and answers the following question: Does analysts' experience creates price reaction? I show that, for experienced analysts, the frequency of small positive forecast errors is larger than the frequency of small negative forecast errors. I also find that firms followed by experienced analysts display more pronounced post-earning announcement drift and higher trading volume at the announcement day as well as the following days. I infer that experienced analysts may have more significant impact on prices and trade volume. A possible explanation is that they do so by adjusting their forecasts and by reporting downward biased earnings forecasts.

This paper discusses the empirical relation between stock returns, dispersion, and short sale constraints. Unconstrained and low level of opinion divergence stocks tend to generate high returns, low idiosyncratic and total risks, display low growth rates and low leverage ratios. Three and four factors models, as well as liquidity factors, cannot account for these high abnormal returns.

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