Belief Dispersion among Household Investors and Stock Trading Volume

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Abstract

We study the effects of belief dispersion on stock trading volume. We focus on beliefs of household investors, and how their disagreements on macroeconomic variables influence market-wide trading volume. We show that greater belief dispersion among household investors is associated with significantly higher stock market trading volume, and significantly higher mutual fund flows. The relationship remains strong after controlling for the disagreements among professional forecasters and stock analysts. Further, we find that the belief dispersion among household investors who are more likely to own stocks has more pronounced effects on trading volume, suggesting a causal relationship. The relationship is also stronger between household belief dispersion and trading volume of large cap stocks, which are more visible to household investors. Finally, greater "belief jumbling," or the dispersion of belief changes over a given period, is also related to more active trading during the same period. Overall, our results lend support to predictions of models with heterogeneous beliefs and highlight the importance of understanding household financial decisions.

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1 Introduction

In a standard representative agent model, an equilibrium asset price clears the market, but no trading occurs in the market because all investors are assumed to be identical. Trading arises in models where investors have different endowment levels, portfolio positions, preferences, or beliefs. This paper presents an empirical analysis on how heterogeneity of beliefs, or disagreement, affects stock trading volume. We address the effects of two types of disagreement—dispersion of belief distributions at a given point in time and dispersion of belief changes over time—on the trading volume of the entire stock market. For convenience, in the remainder of the paper, we refer to the former type of disagreement as "belief dispersion" and to the latter type as "dispersion of belief changes."[1] We focus on the effects of belief dispersion on trading volume, but also present suggestive results on how dispersion of belief changes influences trading volume.

Indeed, the theoretical significance of disagreement among investors on trading volume has been appreciated at least since Varian (1985) and Karpoff (1986), which show that trading arises if investors interpret signals differently or if they interpret signals in the same way but start with different prior beliefs. In the ensuing years, an extensive literature has examined whether the model predictions hold empirically. Most of the existing literature consists of event studies that focus on how the trading of securities of individual firms or industries is affected by disagreement among professional investors, typically within a short period around the time of earnings releases or other major corporate news announcements. To the best of our knowledge, little has been done in studying how disagreement among investors about the outlook for key macroeconomic indicators can influence market-wide trading volume.

Furthermore, beliefs of household investors have been largely unexplored despite households' significant participation in the stock market. According to the Flow of Funds Accounts released by the Federal Reserve, household investors directly own about 40% of outstanding equities in the U.S. and hold about an additional 20% of outstanding equities through mutual funds. Campbell (2006) summarizes the importance and challenges facing the growing field of household finance, whose importance was only accentuated during the recent housing/financial crisis. Thus, it is important to understand how household investors may

[1] Dispersion of belief changes is often dubbed "belief jumbling," a term used in Karpoff (1986) and Bamber, Barron, and Stober (1997).

influence stock trading volume, and further more, if household's belief dispersion contains information over and beyond that of the professional forecasters or stock analysts.

Relative to previous studies, our paper has five distinct features. First, using the Thomson Reuters/University of Michigan Surveys of Consumers (SCA), we study the beliefs of household investors, instead of professional analysts. Second, instead of firm- or industry-specific beliefs, we focus on beliefs about key macroeconomic variables—such as business conditions, unemployment, and interest rates—that potentially influence the level and riskiness of future dividend flows and discount rates. Accordingly, the trading volume we are interested in is the market-wide volume, instead of that of a specific firm or industry. Third, because the SCA data have information on household economic and demographic characteristics, we are able to examine whether the trading volume effects of belief dispersion among certain consumers vary with their propensity of owning stocks. Fourth, instead of event studies that typically focus on short periods of time bracketing some corporate news announcements, our study explores a much more extensive sample period of nearly 30 years (covering from late 1970s to mid-2000s). Fifth, the SCA has a semi-longitudinal structure that allows us to directly measure investors' belief changes over time and the dispersion of the belief changes. Therefore, our analysis also speaks to the nature of the relationship between the dispersion of belief changes and trading activities, a question most of the existing work has not addressed (with Barron (1995) and Bamber, Barron, and Stober (1997) being two exceptions).

Our results suggest that greater disagreements among household investors, measured by either belief dispersion or dispersion of belief changes, are associated with higher stock market turnover rates. These positive effects are both statistically and economically significant. For example, an increase of one standard deviation in the dispersion of consumers' composite expectations implies an increase in the detrended monthly turnover rate in the entire stock market by 22.7% of its standard deviation.

Because beliefs of household investors (and the dispersion among them) are potentially correlated with those of professional analysts, we are interested in whether household belief dispersion introduces any information explaining stock trading in addition to that conveyed in belief dispersion among professional analysts. We calculate belief dispersion of professionals from "Survey of Professional Forecaters", "Blue Chip Financial Forecasts" and I/B/E/S analyst forecasts of earnings. We pit them against our dispersion measure from the household survey and show that household dispersion shows more distinctive counter-cyclical pattern. We then put the belief dispersion measure from both household and professional surveys in our regression model, and show that the baseline result holds well after controlling for one or all three of the dispersion measure for professional forecasters. This suggests that belief dispersion among household investors does provide extra information, and has a marginal impact on stock trading volume.

As an alternative proxy of household trading volume, we calculated gross level of fund flow for retail mutual funds. We find that belief dispersion among household has a similar positive relationship with fund flows. Thus, dispersion of beliefs among household investors affect stock market trading volume either directly or indirectly through mutual funds.

For robustness, we show that our results hold under alternative measurements of trading volumes and belief dispersion. For example, we calculate trading volume from only two of the exchanges, NYSE and AMEX, to address the double counting issue of NASDAQ trading volume (Atkins and Dyl 1997) and (Anderson and Dyl 2005). We also experimented with different detrending method for the turnover measure, and our empirical results are robust to all of that. [2] For belief dispersion, we experimented with standard deviation based measure and our own weighted herfindale measure with different weights for modal outcomes, the results largely remains.

To examine whether the statistical correlations speak to any causal relationship between trading volume and belief dispersion, we conduct two split sample analysis. On the trading volume side, we compare the volume dispersion sensitivities of stocks of different market cap, a proxy for retail participation. We find household belief dispersion to be most related to trading volumes of large cap stocks, which are likely more visible to household investors. On the belief dispersion side, we compare among household with different demographic charaterisics. We find that belief dispersion among household investors who are more likely to participate in the stock market have stronger effects on trading volume.

Finally, our paper also makes a methodological innovation in measuring investor disagreements when beliefs are reported as categorical, instead of numerical, values. Specifically, we introduce the weighted Herfindahl index to measure dispersion of ranked categorical variables. We show that the ability to weight outcome differently allow us to exploit information contained in survey results better. By giving more weights to predicted future outcome that

[2] We settle on cubic-detrending for our baseline results to be conservative.

are different from current status-quo, we are able to reduce noises from lazy answers where surveyed household simply check the modal answer "unchanged" to avoid taking a stand. We show that our constructed series of household investors' belief dispersion tends to be significantly countercyclical—disagreements tend to rise when the economy is in recessions. The time series pattern is stronger in our household-based disagreement measure than other professional forecasts.

The paper proceeds as follows. Section 2 briefly summarizes the previous theoretical contributions on the relationship between investor belief heterogeneities and trading volume, followed by motivating our analysis through a review of the existing empirical literature. Section 3 describes the data. Section 4 introduces our measures of belief dispersion and dispersion of belief changes and presents summary statistics. Section 5 presents the main empirical results and robustness analyses. Section 6 concludes and outlines a future research agenda.

2 Related Literature

One of the most surprising and elegant pieces of economic theory is the No-Trade theorem (Milgrom and Stokey 1982). The theorem states that in a speculative market composed of fully rational agents with identical prior beliefs, no trade will occur in equilibrium, even in the presence of asymmetric information. The prediction is obviously not meant to be realistic, but it provides a starting point to any attempt to answer the question—why do people trade in financial markets?

Tirole (1982) describes the conditions under which the No-Trade theorem does not hold: (1) there exist irrational traders, or noise traders who trade for liquidity reasons; (2) some investors trade for hedging or diversification purposes; and (3) agents have different prior beliefs. Regarding the first possibility, a rapidly growing literature in psychology and behavioral finance has documented the behavioral biases of human beings in making financial decisions. Hirshleifer (2001) and Barberis and Thaler (2003) provide thorough reviews of earlier contributions. More recently, Scheinkman and Xiong (2002) suggest investor overconfidence as a potential source of heterogeneous beliefs, a hypothesis that finds empirical support in Statman, Thorley, and Vorkink (2006).

Outside of the school of behavioral finance, a large body of the literature investigates trading volume under Tirole's second assumption, allowing agents to have different endowments or different preferences. In such an environment, trade happens because investors form their optimal portfolios based on their budget constraints and risk tolerances which are different across individuals. For example, Wang (1994) introduces both heterogeneous investment opportunities (endowments) and asymmetric information in a competitive market, and identifies a link between the nature of heterogeneity among investors and the dynamics of trading volume. The challenge that the heterogeneous endowment argument faces is that it can generate only one round of trade, after which no further trade will take place.

In this paper, we focus on the third condition outlined by Tirole (1982) under which trade arises, namely, agents having different beliefs. The argument is, first and foremost, empirically sound. Considering "the glass is half full or half empty" argument, it speaks to the deep psychological roots of the dispersion of human optimism or pessimism. As Hong and Stein (2007) argue, "disagreement models uniquely hold the promise of being able to deliver a comprehensive joint account of stock prices and trading volume, which we consider to be one of the highest priorities for theoretical work in asset pricing."

Various theoretical papers have demonstrated how differences in beliefs can be linked to trading volume. Karpoff (1986) is one of the seminal early contributions. Specifically, he shows that both different interpretations of the same information and different prior beliefs can stimulate trading activities.[3] Hence, two different aspects of belief heterogeneity—(1) dispersion of prior beliefs and (2) dispersion of belief changes—can stimulate trade, we address both in this paper.

By no means is this paper the first attempt at providing empirical evidence for Karpoff's theory. Rather, we are motivated by the gaps in the existing, albeit vast, empirical literature. We highlight several major ways in which our paper improves upon and extends the previous empirical work.

First, most existing empirical studies do not measure investor beliefs directly. Instead, they use financial analysts' forecasts as an approximation and estimate their dispersion. However, Dinh and Gajewski (2007) point out that such proxies can be inaccurate since they represent only a small proportion of economic agents, who are often more informed and more sophisticated than most market participants. In addition, analysts' forecasts may be

[3]For subsequently developed models with different prior beliefs, see Detemple and Murthy (1994); for models in which investors have different ways of updating their posterior beliefs, see Harris and Raviv (1993) and Kandel and Pearson (1995).

influenced by their interests and incentives and thus can be biased. For example, analysts' desire to win investment banking clients may lead them to adjust their forecasts to avoid earnings disappointments (Chan, Karceski, and Lakonishok 2003). Moreover, Hong, Kubik, and Solomon (2000) find that analysts, especially inexperienced ones, herd in their forecasts because of career concerns.

Effort has been made to characterize belief heterogeneity in a more direct and comprehensive way. Bessembinder, Chan, and Seguin (1996) consider the open interest of S&P 500 index futures a proxy for dispersion of traders' opinions regarding underlying values and find it positively related to trading volume. Their approach, although probably covering a broader set of investors, is still not a direct measure of belief. Goetzmann and Massa (2005) construct an opinion dispersion index from information about 100,000 retail investors and find the index positively related to contemporaneous trading volume and stock return. Furthermore, they find that dispersion of opinion among retail investors Granger-causes dispersion of opinion among analysts. However, their paper does not measure investors' opinion per se; instead, it uses investor characteristics, such as age, income, and occupation, to construct the dispersion index.

In this paper, we address these concerns by constructing metrics of belief dispersion using data of self-reported expectations directly collected in a nationwide representative survey of consumers, who, unlike professional analysts, are largely immune to the aforementioned conflict of interests. Despite an increasing presence of household investors in the stock market, to the best of our knowledge, this paper is the first study on how belief dispersion among household investors may affect trading volume in the stock market.

Furthermore, this paper is among the first to examine the effects of dispersion of macroeconomic beliefs on trading volume. Previous studies have largely focused on dispersion of earnings forecasts of individual firms, without considering concurrent dispersion of beliefs regarding future macroeconomic conditions. However, expectations on future macroeconomic conditions (such as interest rates and unemployment) play a pivotal role in shaping investors' strategies and portfolio choices as these variables tend to influence the level and riskiness of future dividend flows of all firms and the interest rate at which future dividends are discounted.

Most prior studies examine specific events, such as the releases of corporate earnings, and beliefs and trading volumes are measured over a short period of time bracketing such events (Comiskey, Walkling, and Weeks 1987, Ziebart 1990, Lang and Litzenberger 1989). Nevertheless, agents do not trade only on their opinions about earnings releases. Investors' opinions about the economy and their perspectives on interest rates and employment should all be critical in forming their opinions about financial investment and trading strategies. One immediate piece of supporting evidence is the large systematic outflows and inflows of money in different sectors of the mutual funds industry in the wake of the current financial crisis. In reality, agents receive new information on a continuous basis, especially information concerning the economy. As new information comes, investors update both their short- and long-term outlooks for the economy and financial markets. Thus, it is an empirical question to what extent each piece of information matters in generating trades.

The household survey we use also presents a unique opportunity for studying the potential differences in how belief dispersion affects trading volume across subgroups of consumers that are different by their propensity of investing in stocks. If indeed, a higher degree of belief dispersion among investors causes more active trading, we expect such an effect to be most pronounced for dispersion among households that are most likely to invest in stocks, and most subdued for dispersion among households who invest little in stocks.

Most prior empirical research looks at only the static aspect of belief dispersion and ignores the dynamics of beliefs, with Barron (1995) and Bamber, Barron, and Stober (1997) being two of the few exceptions. The two papers explicitly test Karpoff (1986) by illustrating the positive relationship between trading volume and differential belief revisions among investors. Our paper shares a similar spirit. Exploiting the longitudinal structure of the survey allows us to further explore how dispersion in belief changes within a given period of time affects the trading activities during the same time.

By looking at the dispersion of investor beliefs directly, the paper is related to growing literature that look at the asset pricing implications of belief dispersion. Ehling, Gallmeyer, Heyerdahl-Larsen, and Illeditsch (2013) use the same consumer survey data, and look at the impact of disagreement about inflation on the level and volatility of both real and nominal yields. Carlin, Longstaff, and Matoba (2012) look at disagreement among Wall Street mortgage dealers about prepayment speed, and find it to be related to expected returns, return volatility and trading volume in the mortgage-backed security market.

The paper is also related to growing literature that look at the financial decisions of household or retail investors. Using a unique databae, Kelley and Tetlock (2013) study the role of retail investors in stock pricing. They find supporting evidence that retail investors' aggressive orders convey novel cash flow information and their passive orders provide liquidity to the market, both contribute to market efficiency. Amromin and Sharpe (2012) analyze stock market beliefs and portfolio choices of household investors. We contribute to this literature and argue that household investors are not negligable. Their beliefs about the macro economy is strongly related to stock market trading volume.

3 Data

3.1 Surveys of Consumers

We use the respondent-level data of the Thomson Reuters/University of Michigan Surveys of Consumers (SCA) to measure household investors' beliefs and their dispersion. The SCA is conducted by the Institute of Social Research at the University of Michigan. The most influential SCA products is the Index of Michigan Consumer Sentiment. Introduced in the late 1940s, the index has established itself as one of the most widely followed indicators that measure households' sentiments about current and future economic and business conditions. Validation studies have shown that the information collected in the SCA predicts the dynamics of the nationwide economy remarkably well.[4]

The SCA has been conducted monthly since 1978, and in recent years a minimum of 500 consumers have been surveyed each month from a phone facility in Ann Arbor, Michigan. The consumer-level data we use cover more than 30 years.[5] The SCA provides a short panel structure. About 40 percent of the respondents were surveyed again six months after their first interview, a feature we will exploit to study the effects of dispersion of belief changes on trading volume. However, these consumers were not called again after the follow-up interview.

Each month, about 50 core questions are asked to collect information broadly related to consumers' assessments of current economic conditions and their expectations about the fu-

[4]The Index of Michigan Consumer Sentiment is included in the Leading Indicator Composite Index published by the Bureau of Economic Analysis because of its "economic significance" and "statistical adequacy." For more information about the SCA, see the documentation at the SCA webpage at `www.sca.isr.umich.edu/main.php`.

[5]Although the survey started shortly after World War II, respondent-level data for the years before 1961 are not publicly available. For the period from 1961 to 1965, the respondent-level data are available only in February; for 1966, they are available in February and August; and for 1967 to 1977, the respondent-level data are available quarterly in February, May, August, and December.

ture of their households and the national economy.[6] Moreover, the SCA collects information about key demographic characteristics and the economic status of sampled consumers. We will study the belief dispersion (and its changes) about future business conditions, personal financial conditions, unemployment, and interest rates. Table 1 summarizes the variables on which our study focuses. We keep all original variable names as they were assigned by the SCA staff. Four of the five questions—PEXP, BEXP, UNEMP, and RATEX—are about consumers' expectations in the near term, typically within the next 12 months. They survey households' short-term expectations on personal finance, business conditions, the unemployment rate and interest rates respectively. The only question regarding long-term expectations is BUS5, which is expectations about business conditions during the next five years.

Most SCA questions have categorical, instead of numerical, answers.[7] The predominance of categorical questions may be due to the fact that they are easier to answer for typical household respondents. For example, when asked about unemployment expectations, consumers are asked to choose from three answers—"more unemployment," "about the same," and "less unemployment"— rather than to specify an unemployment rate. Similarly, when asked about future business conditions, consumers choose from "better off," "same," and "worse off." One advantage of focusing on categorical responses is that it avoids the influence of "wild answers." However, when beliefs are so represented, constructing measures of belief dispersion (and dispersion of belief changes) is less straightforward. In Section 4, we will discuss the technique used to measure the dispersion of the categorical answers.

3.2 Forecasts by Profesionals

Earlier research has documented that dispersion of beliefs regarding corporate earnings among professional analysts can influence trading activities to a large extent. Presumably, wider belief dispersion among professional analysts regarding future macroeconomic conditions can also induce higher trading volume, pressing us to study whether belief dispersion

[6]From time to time, additional questions, known as the "riders", were added in special modules. These questions, though interesting and potentially closely related to stock market trading activities, are typically asked only for a limited number of months and may not be asked at regular monthly frequency.

[7]The only exceptions are two questions about future inflation rates, for which consumers are asked to give numerical answers. We did not study the effects of dispersion in inflation expectations because, relative to dispersion of categorical responses, dispersion of numerical responses in consumer surveys are more prone to be influenced by "wild" answers. For example, the cross-sectional standard deviations of inflation expectations in the SCA are much higher than those in the Survey of Professional Forecasters.

among household investors has any net extra effects on trading volume beyond the extent to which their belief dispersion is correlated with those among professional forecasters.

We use three different measures to measure beliefs of professionals

- Survey of Professional Forecasters

  The Survey of Professional Forecasters (SPF) is a survey for professional investors on their views about macroeconomic conditions. It is currently conducted by the Federal Reserve Bank of Philadelphia.[8] The SPF is different from the SCA in a number of aspects. First, the SPF is conducted quarterly whereas the SCA is a monthly survey. Second, the survey method and questions in the SPF are somewhat different from those in the SCA. In particular, unlike the categorical responses given to the qualitative questions asked in the SCA, SPF respondents are asked to report the numerical value of their forecasts, among others, of GDP, industrial production, corporate profit, and unemployment rate.

- Blue Chip Financial Forcasts

  Blue Chip Financial Forecasts are survey data published by a monthly newsletter. Participants of the surveys are typically economists at large banks. The main forecasts variables are interest rates. A couple of macro variables are also forecasted. Similar to the SPF, the Blue Chip forecasts represents beliefs of sophisticated professionals. Our Blue Chip data start in July 1984, which is a bit later the SCA or SPF data. Earlier part of the Blue Chip data were digitized from paper version of the newsletter.

- I/B/E/S Analyst Forecasts of Corporate Earnings I/B/E/S provides detailed analyst-stock-level forecast of coporate earnings per share (EPS) and other key variables. We aggregate the dispersion of forecasts for each stocks to get market level dispersion of analyst's belief about the stock market in general.

To control for belief dispersion among professional forecasters in a parsimonious way, we separately estimate the belief dispersion time series for each question in the SPF and Blue Chip Survey and synthesize them into the first principal components for the two survey respectively.[9].

[8]The survey was conducted by the National Bureau of Economic Research before being transferred to the Federal Reserve Bank of Philadelphia in early 1990s.

[9]See Section 5 for details.

3.3 Trading Volume

We use the market-wide stock turnover rate (the total number of shares traded in a period divided by the average total number of shares outstanding during the period) as a measure of trading volume in our estimation. Normalizing trading volume with shares outstanding allows us to abstract from increases in volume that are due mainly to the growth of the economy or the stock market. The turnover measure has been used in various studies, such as Campbell, Grossman, and Wang (1993) and LeBaron (1992)Data on both the number of shares traded and shares outstanding are from the Center for Research in Security Prices. In our baseline analysis, we aggregate the monthly trading volume and shares outstanding of all securities traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ.

Our sample covers the period from January 1978 to the end of 2011. As shown in the upper panel of figure 3, turnover rates in the U.S. stock market steadily increased during our sample period. Many explanations have been proposed to explain this trend. For example, Smidt (1990) suggests that the long-run trend in equity turnover can be attributed to transaction cost changes. A Dickey-Fuller test suggests that the series is trend stationary. The middle panel of figure 3 shows the cubic detrended series of turnover, which is used in our baseline analysis.[10] The series has a mean equal to zero and a standard deviation equal to 0.024. We note that the detrended series exhibits a certain level of persistence (autocorrelation coefficient above 0.6), which we will control for in our estimations.

3.4 Fund Flow and Control Variables

Our fund flow data is from Investment Company Institute. Monthly flow to equity market are calculated as the sum of inflow and outflow to equity funds, normalized by total size of equity mutual funds. The fund flow data start from Jan. 1984. Lower panel of Figure 3 shows the monthly time series of equity fund flows.

We also use S&P 500 index return, S&P 500 index volatility as control variables. Both of them are calculated from CRSP data. In addition, we control for stock market liquidity in the model. We download the Pastor-Stambaugh Liquidity series as in Pastor and Stambaugh (2003) from WRDS. One can see from Figure 4 that the big downward spikes in the liquidity

[10] In robustness analysis, we vary the detrending method to allow for trends of various polynomials.

measure does correspond to period of market liquidity crisis. The measure is on average negative, the more negative the measure is, the less liquid the market is.

4 Measures of Belief Dispersion and Dispersion of Belief Changes

4.1 Dispersion Measures

To measure dispersion of beliefs in the SCA that are denoted by categorical values, we construct a weighted negative Herfindahl index. The Herfindahl index has been widely used as a measure of market concentration (see, for example, Neumark and Sharpe (1992)). It is thus natural for us to use it to measure the opposite of concentration—dispersion. Recall that the standard Herfindahl index is defined as

$$H = \sum_{i=1}^{N} p_i^2, \tag{1}$$

where p_i is the share of the i-th element among N elements. The Herfindahl index takes a value between $1/N$ and 1. A lower value of the index indicates greater dispersion.

The standard Herfindahl index treats each of the N elements symmetrically, without taking into account the ordering among the elements. Thus, the distances between elements are equal. However, one important aspect of the SCA data is that different answers are naturally ranked, and hence the distance between answers matters. For example, a sample consisting of 50 percent survey responses that are "better off" and 50 percent "worse off" will yield the same value of standard Herfindahl index as a sample consisting of 50 percent "better off" and 50 percent "about the same" answers, although opinions in the first sample are clearly more dispersed. To explicitly account for such relative distances, we construct (for each survey month) a weighted negative Herfindahl index as

$$WNHI = -\sum_{i=1}^{N} \omega_i p_i^2, \tag{2}$$

where ω_i is a weight assigned to element i. We give lower weights to elements closer to the polars and higher weights to elements in the middle. Specifically, in our baseline analysis, we let the weights on the answers of "better off" and "worse of" be equal to one and the weight on the answer of "about the same" be equal to two. The weights were chosen to generate lower Herfindahl index values (higher dispersion) for belief distributions with more polar answers. We also alter the weights as part of the robustness analysis, and the results were not qualitatively sensitive to the weight choices. Finally, for expositional convenience, we take the negative value of the index to make it an increasing function of the degree of belief dispersion—higher value of the index indicates greater dispersion.

4.2 Measures of Dispersion of Belief Changes (DBC)

Bamber, Barron, and Stober (1997) define belief jumbling as "information-triggered belief revisions that differ across investors and change an individual's expectation relative to the distribution of expectations held by others (i.e., the reordering of beliefs across investors)." Similar to their approach, we construct a measure of dispersion in belief changes that can capture the reordering of beliefs across investors.

In the SCA surveys, about 40 percent of the consumers are surveyed again six months after they were surveyed the first time. We can thus track consumer belief changes over a six-month interval. The limitation of the data is that, for each consumer, only one observation of belief change was available because the consumers are not contacted again after the second interview.

Recall that all of the SCA questions we study have categorical answers. The SCA typically asks the consumer whether the future of the economy will be better, worse, or about the same or whether an economic indicator, such as the interest rate and the unemployment rate, will go up, go down, or remain the same. To measure belief changes in qualitative expectation variables, we construct a "belief crossing" variable. This variable takes the value of -1 (1) if at month m the consumer expected the economy to be better (worse), but in six months, when surveyed again, the consumer instead expected the economy to be worse (better). Similarly, we define the belief crossing variable to be -1 (1) if at month m the consumer expected an economic indicator to be higher (lower) in the future, but in six months, when surveyed again, the consumer instead expected the same indicator to be lower (higher). If the consumer's answer was unchanged six months later, the belief crossing variable takes the value of 0. For all expectation variables, if either in month m or month $m + 6$, the consumer reported "to be the same," the belief crossing variable would be set to 0 as well. More specifically, we defined $Crossing$ as the following:

$$Crossing = \begin{cases} -1 & \text{if better}\rightarrow\text{worse (higher}\rightarrow\text{lower)} \\ 0 & \text{if better}\rightarrow\text{the same (higher}\rightarrow\text{the same)} \\ 0 & \text{if better}\rightarrow\text{better (higher}\rightarrow\text{higher)} \\ 0 & \text{if the same}\rightarrow\text{better} \\ 0 & \text{if the same}\rightarrow\text{the same} \\ 0 & \text{if the same}\rightarrow\text{worse} \\ 0 & \text{if worse}\rightarrow\text{worse (lower}\rightarrow\text{lower)} \\ 0 & \text{if worse}\rightarrow\text{the same (lower}\rightarrow\text{the same)} \\ 1 & \text{if worse}\rightarrow\text{better (lower}\rightarrow\text{higher)} \end{cases}$$

This is a conservative measure of belief changes in the sense that it considers only those about-face changes of beliefs from one end of the spectrum to the other as a belief change. When we count changes from "the same" to "better" or to "worse" (and the reverse) as belief changes but with a smaller weight, our results are qualitatively preserved. The dispersion of belief changes (DBC) over six months is defined as the standard deviation of the belief crossing measure for each given time period

$$DBC_m = \sigma(Crossing_{i,m}) = \sqrt{\frac{\Sigma_{i=1}^{N_m}(Crossing_{i,m} - \overline{Crossing_{i,m}})^2}{N_m}}, \tag{3}$$

where $Crossing_{i,m}$ is the crossing of agent i's belief between month $m-6$ and m, which takes the value of (-1,0,1) and N_m is the number of survey respondents with valid belief change measures.

4.3 Composite Dispersion Measure

Figure 1 presents the time series belief dispersion, measured using $WNHI$, for each SCA questions. Recall that higher $WNHI$ (closer to zero) suggests a more dispersed distribution of beliefs. It is interesting to observe that beliefs about longer-term business conditions in the next five years, $BUS5$, are more dispersed than beliefs about other shorter-term economic conditions, such as $BEXP$, which represents the expectations about business conditions after one year. The $WNHI$ values for $PEXP$, $RATEX$, and $UNEMP$ suggest that beliefs on those variables are dispersed to similar extents as is $BEXP$. In addition, three of the five series of belief dispersion, $PEXP$, $RATEX$ and $UNEMP$, exhibit strong counter-cyclicality. The peaks of dispersion of expectations about near-term economic conditions, interest rate, and unemployment largely coincide with the dates of recessions as defined by the National Bureau of Economic Research. However, we find less-strong cyclical dynamics in the belief dispersion for expectations about personal financial and longer-term business conditions.

Expectations on various macroeconomic indicators held by the same investor are likely correlated (people expecting lower unemployment also tend to expect better business conditions), potentially making dispersion of beliefs on these macroeconomic indicators also correlated. To summarize the information contents contained in the five series of belief dispersion, following Buraschi and Whelan (2010), we compute the principal components of these series. We will focus on the first principal component, as it accounts for over 50 percent of total variance, and each of the successive principal components explains no more than 20 percent of total variance. As shown in the lower right panel of Figure 1, the first principal component also exhibits pronounced counter-cyclicality.

We apply similar technique to generate composite measure of belief dispersion of professional forecastors in the SPF and Blue-Chip Surveys.

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5 Empirical Results

5.1 The Counter-cyclicality of Dispersion Measures

Figure 2 plots the time series of SCA household belief dispersion and three professional belief dispersion measures. One can see that all of them display some level of counter-cyclicality. Such counter-cyclicality is especially pronounced in the belief dispersion of household beliefs. Patton and Timmermann (2010) also document this counter-cyclicality using data taken from the Consensus Economics Inc. They argue that greater differences in opinion during recession are not due to increased hterogeneity in information signals, but can be related to a shift toward agents putting more weight on their priors.

5.2 Belief Dispersion and Trading Volume

5.2.1 Baseline Analysis

We estimate the following model for stock markt turnover:

$$Turnover_m = \alpha + \rho Turnover_{m-1} + \beta WNHI_m^J + \gamma Mean_m^{ICE} + \delta_1 R_m + \delta_2 \sigma_m + \delta_3 LIQ_m + \eta Post2007 + \sum_{i=1}^{11} \psi_i I_{i=m} + \varepsilon_m, \quad (4)$$

where $Turnover_m$ is the cubic-detrended turnover for month m. We include one lag, $Turnover_{m-1}$, of the dependent variable to absorb some of the autocorrelations exhibited in the detrended turnover series. We control for the mean levels of the expectation index, ICE. The index is constructed by the SCA staff as a summary of investors' expectations about economic fundamentals and thus is likely to affect stock market trading activities. R_m is the contemporaneous gross return in the S&P 500 index. Many papers look at the relationship between stock returns and trading volume (see for example,Campbell, Grossman, and Wang (1993) and Llorente, Michaely, Saar, and Wang (2002)). We also control for stock market volatility σ_m and stock market liquidity LIQ_m, which may all be related to market trading volume. We include a dummy $Post2007$ which takes the value of 1 if the year is equal or after 2007. This is due to the fact that market trading volume exploded during the financial crisis, and perticularly so for stocks with the greatest level of institutional holdings (Chordia, Roll, and Subrahmanyam 2011). The dummy can help us capture any volume shift happened around the time of the crisis. In addition, we include a vector of monthly dummies to control for seasonal factors. Hong and Yu (2009) find that trading volume in summer vacation months is significantly lower than that in other months. In contrast, trading around year-end could be higher, driven by tax-related reasons. These seasonal fluctuations can be captured by the monthly dummies, denoted as $\sum_{i=1}^{11} \psi_i I_{i=m}$ in Equation 4.

In the above specification, the parameter of interest is β. Recall that we construct the $WNHI$ so that higher $WNHI$ implies wider belief dispersion. Should wider belief dispersion indeed induce larger trading volume, we will observe $\beta > 0$ in Equation (4). Table 4 reports the estimation results. All standard errors are adjusted for autocorrelations and heteroskadasticity using the Newey-West method with first-order autocorrelation.[11] We find that in Model 1.a through Model 1.d, where dispersion of opinion from different survey sources are included individually, β-coefficients are all positive and highly statistically significant. indicating that more-dispersed beliefs about future economic conditions among

[11] Allowing for higher orders of autocorrelation does not change the results qualitatively.

household investors, professional forecastors or financial analyst are associated with higher stock market turnover. The effects are not only statistically significant but also economically significant. For example, if the dispersion among household investors increases one standard deviation , the monthly turnover rate will increase 0.56 percentage point, or about 22 percent of the standard deviation of the detrended turnover rate. An increase of one standard deviation in the belief dispersion among $IBES$ analysts, Blue-Chip economists and SPF profesionals correspond to increase in turnover of 9.5 percent, 12.1 percent and 10.9 percent respectively.

For Model1.a through Model 1.d reported in Table 4, we find that comntemporaneous stock market returns are weakly positively correlated with turnover rates. The coefficient for $S\&PReturn$ is significant for Model 1.a and Model 1.b, insignificant for Model 1.c and weakly significant for Model 1.d. This weak finding is likely due to the lower sample frequencies (monthly) that our study focused on, compared with those in the literature, which are typically daily. In addition, we find that the mean level of the ICE variable, $Mean(ICE)$, has a weakly positive effect on turnover rates. Consistent with the literature, S&P 500 index volatility (annualized) is significanly positively related to stock market trading volume. However, stock market liquidity seem to be negatively related to stock market trading volume, which is likely due to the fact that financial crisis, typically time of high trading volume, are also time of low market liquidity.

5.2.2 Compare with Professional Forecasters

It is well documented that disagreements among professional analysts can affect trading volume. It is possible that the degree to which household investors disagree with each other is correlated with the belief dispersion among professional analysts. Thus, it is important to understand whether belief dispersion among household investors carries any additional information that is helpful for understanding the market-wide trading volume beyond dispersion among professional analysts.

In Model 2 through 4 of Table 4, We cumulatively add the belief dispersion variables for prefessional forecasters in the order of IBES Analyst dispersion, Blue-Chip forecasts dispersion and SPF prefessional forecastors disperion. We find that once household investors are pit against professional forecasters, only the belief dispersion among household investors remain highly significant. Suggesting that belief of household investors carries information over and beyond that of the professional investors.

5.2.3 Belief Dispersion and Mutual Fund Flow

How do household investors trade on their belief. Many of them are more likely to invest indirectly in the stock market through stock mutual fund. Are household investors' belief dispersions associated with higher level of retail mutual fund flows? We repeat the same exercise on our mutual fund flow variable, and the results are reported in Table 5. We find that results are quite similar to those on stock market trading volume. Household belief dispersion is highly significantly positively related to mutual fund flow, even if professional forecaster's belief dispersions are also considered.

5.2.4 Robustness

While presenting our baseline results, we have made several choices in organizing the data for parsimonious analysis. Are our empirical results sensitive to the way we calculate turnover rates, belief dispersion and model specifications? We implement a sequence of robustness analyses to show that the relationship presented between belief dispersion and market-wide stock turnover rate is highly robust. The estimated β coefficients of varying specifications are summarized in Table 6.

We first try vary the way the trading volume variable is constructed. For example, we exclude tradings in NASDAQ to take into consideration that NASDAQ interdealer trades are double counted. We then try three different detrending methods to remove trend elements from the trading volume time series. These three methods are linear detrending, quadratic detrending and Baker-Stein detrending. One can see that variation in dependent variable does not seem to change the result much. β remains highly statistically significant.

We then experiment with giving different weights, ω_i in Equation (2), to survey answers that are "about the same" when we compute the weight Herfindahl index. In our baseline analysis, we give a weight of 2 to such answers. We now try a smaller value of the weight, 1.5. We also present the result where the ordering of the answers is not taken into account (ω = 1). We also try to code our categorical answers into simple numers like -1, 0, 1, and then use standard deviation as an alternative measure of dispersion in responses to the question. Finally, we try weight respondents' answers by their imputed likelihoold of owning stocks before calculating the $WNHI$ of the answers.

As shown in the bottom half of Table 6, most coefficients remain positive and are both statistically and economically significant. It is worth nothing that reducing the weight on central answer does seem to weaken the results a bit and using standard deviation of numerically coded categorical answer seems to yield the weakest result. We think this suggest that our $WNHI$ measure, by having the flexibility in weighting, allows us to capture the dispersion of opinion better. Finally, giving ownership weight seems to enhance the results more, which is consistent with the idea that it is the belief of those that owns stocks that matters.

Overall, the results seem to be very robust to variations in the constructions of turnover and dispersion variables.

5.3 Suggestive Evidence on Causal Relationship

So far the our findings have being focusing on the correlation between belief dispersion among household and stock market trading volume. Theory sugests that the relationship should be not only postive, but also causal. We split the sample in different ways to show suggestive evidence of such relationship. If the dispersion of belief among household investors causes more trading, we should expect the trading volume of stocks that household investors favor, to be more sensitive to belief dispersion among household investors. In addition, the dispersion of belief among the subgroup of household that are more likely to own stocks should also have a stronger relationship with stock market trading volume. We test these two hypotheses correspondingly.

5.3.1 Anaysis by Market Cap

Retail investors typically have limited information about stocks (Merton 1987). Thus, household investors' trading activities are likelly associated with the visibility of the stocks. Natually, stocks with larger market caps are likely those followed by more news media and analysts, and have higher visibilities to retial investors. Da, Engelberg, and Gao (2011) empirically confirmed this relationship. They find that their direct measure retail investor attention to stocks, Google search volume on the stock ticker, is significantly positively related to size of the stock. We hypothesis that trading volumes of more visible stocks, the large cap stocks, are more sensitive to the dispersion of opionion among household investors.

Table 7 confirm the hypothesis. [to be finished]

5.3.2 Analysis by Demographic Characteristics

Investors of different demographic and socioeconomic characteristics have different propensities of investing in stocks. For example, the Survey of Consumer Finances data show that prime-age, more educated, white, and higher-income investors are more likely to hold stocks (also, see Hong, Kubik, and Stein (2004)). To examine whether the observed correlation between household investors' belief dispersion and trading volume speak to any causal relationship, we further study the relationship between trading volume and belief dispersion among subgroups of investors who are different in their likelihood of holding stocks. If it is indeed that wider dispersion of beliefs causes higher trading volume, such an effect should be stronger for dispersion among households that are more likely to participate in the stock market. In particular, we expect that belief dispersion among prime-age, college educated, white, and high income investors to affect market-wide trading volume more significantly.

We compute the belief dispersion series and re-estimate Equation (4) for each subgroup of investors. The estimates of β coefficients for these demographic and socioeconomic subgroups are summarized in table 8. As the results indicate, the estimated effects of belief dispersion on trading volume tend to be more pronounced in magnitude and more statistically significant for the groups of household investors that are more likely to own stocks. More specifically, the estimated coefficients on household belief dispersion for the prime-age, at least high school educated, white and higher-income investors are uniformly larger and of higher statistical significance than those for investors who are young, have no high school degree, black, and have the lowest income. Such a stark contrast in the estimates is suggestive of a causal relationship between belief dispersion and trading volume.

5.4 Trading Volume and Dispersion of Belief Changes

We now turn our attention to effects of dispersion of belief changes on trading volume. We replace the dispersion measure $WNHI$ in Equation (4) with the measure of dispersion of belief changes, DBC, which we defined in Section 4.2. The results are presented in Table 9. Recall that in the SCA sample, some respondents were interviewed for the second time six months after the initial interview; the dependent variable is therefore the six-month cumulative turnover rate, and the S&P returns are also quoted for the six-month time period between the two interviews. Because the six-month turnover rates are overlapping, we allow for the residuals to be autocorrelated up to five lags when correcting standard errors using the Newey-West method. In Table 9, β-coefficients in both columns are statistically significant. On balance, the results are broadly consistent with the predictions of Karpoff (1986) and the subsequent empirical findings by Barron (1995) and Bamber, Barron, and Stober (1997) which state that the extent to which people's belief revisions differ from each other also contributes to the fluctuations of trading volume.

6 Conclusion

This paper implements a direct test of the hypothesis that greater belief dispersion and dispersion of belief changes induce higher trading volume (Varian 1985, Karpoff 1986, Ng 2003, Detemple and Murthy 1994, Harris and Raviv 1993, Kandel and Pearson 1995). Empirical evidence of trading volume's relationship with belief dispersion has been limited due to the difficulty in measuring beliefs; this limitation is even greater for dispersion of belief changes. Most of the prior efforts have focused on studying the beliefs of financial analysts around events such as earnings releases. We contribute to the literature by looking directly at the beliefs of households using semi-longitudinal survey data. We argue that this contribution brings us one step closer to measuring the beliefs of market participants and that this measure is likely immune to the biases that stock analysts may inherently have. Moreover, instead of focusing on informational events such as earnings releases, we focus on consumers' beliefs regarding the economy as a whole, such as future business conditions, future personal financial conditions, interest rate changes and unemployment outlooks.

We have shown broad and robust evidence that stock market turnovers and retail mutual fund flows are positively related to both the dispersion of contemporaneous beliefs about the future economic outlook and the dispersion of changes in beliefs. Belief dispersions of household investors matters for trading volume over and beyond the belief dispersions of professional forecasters or business analysts. Turnovers are more sensitive to dispersion among consumers who fall into the demographic and income groups that are associated with higher stock market participation, which adds credibility to the supposition that these results are not spurious. Moreover, consistent with Karpoff (1986), we find that the dispersion of belief changes ("belief jumbling") over a six-month period is also positively correlated with the cumulative turnover rates during the same time period.

Future research could study capital markets beyond stock exchanges and link forecasters' disagreement on economic indicators to markets that are most relevant to the expectations. For example, one could investigate the relationship between the trading volume in the market for Treasury inflation-protected securities and forecasters' disagreement about future inflation or the relationship between the trading volume in the corporate bond market and disagreement about future corporate bond spreads in the Survey of Professional Forecasters. Such efforts would provide further evidence that belief dispersion and belief jumbling generate trade.

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Table 1: Description of SCA Expectation Variables (all categorical)

Variable name	Description
$PEXP$	Expectations about whether the consumer himself will be better off financially in a year.
$BEXP$	Expectations about the business conditions in the country after one year.
$BUS5$	Expectations about the business conditions in the country during the next 5 years.
$RATEX$	Interest rates expectations— borrowing rates go up or down during the next year?
$UNEMP$	Unemployment expectations—more or less unemployment during the next year?

Table 2: Summary statistics of the dispersion variables

Variable	**Mean**	**Std. Dev.**	**N**
SCA Household Disp	0	1.55	408
SPF Professional Disp	-0.2	1.63	408
IBES Analyst Disp	5.12	1.42	408
Blue-Chip Disp	0	1.81	330

Table 3: Correlation Matrix of Dispersion Measures

Variables	SCA Household Disp	SPF Disp	IBES Analyst Disp	Blue-Chip Disp
SCA Household Disp	1.00			
SPF Disp	0.63	1.00		
IBES Analyst Disp	0.31	0.33	1.00	
Blue-Chip Disp	0.20	0.55	0.56	1.00

Table 4: Turnovers and Belief Dispersion

The table reports turnovers' responses to the dispersion among SCA respondents' beliefs. Dispersion of PEXP, BUS5, BEXP, RATEX and UNEMP are measured using the weighted negative Herfindahl index ($WNHI$). PCA is the first principle component of the dispersion of the other five variables. Independent variables also include monthly dummies. Numbers in parentheses are Newey-West adjusted standard errors. ***, ** and * correspond to significance levels at 99%, 95% and 90% correspondingly. Dependent variable $Turnover$ is measured monthly and is quoted in percentage points. It is also trend adjusted using cubic detrending.

	Model 1.a	Model 1.b	Model 1.c	Model 1.d	Model 2	Model 3	Model 4
L.Detrended Turnover	0.489***	0.506***	0.482***	0.503***	0.477***	0.420***	0.420***
	(0.040)	(0.041)	(0.046)	(0.042)	(0.041)	(0.048)	(0.048)
Mean Expectation	0.038***	0.011	0.014	0.021**	0.037***	0.054***	0.054***
	(0.009)	(0.007)	(0.010)	(0.008)	(0.009)	(0.014)	(0.014)
S&P Return	0.384**	0.343**	0.315	0.334*	0.355**	0.321	0.320
	(0.169)	(0.174)	(0.218)	(0.174)	(0.170)	(0.212)	(0.212)
S&P Volatility	7.543***	7.055***	7.557***	7.357***	7.290***	7.701***	7.675***
	(1.220)	(1.250)	(1.412)	(1.239)	(1.233)	(1.383)	(1.396)
Stock liquidity	−3.229**	−3.778**	−3.586**	−3.212**	−3.434**	−3.299**	−3.314**
	(1.448)	(1.485)	(1.665)	(1.482)	(1.450)	(1.603)	(1.608)
Post 2007	−0.630**	0.050	−0.444	−0.252	−0.566*	−1.087***	−1.076***
	(0.298)	(0.267)	(0.358)	(0.288)	(0.303)	(0.383)	(0.393)
SCA Household Disp	0.359***				0.332***	0.417***	0.415***
	(0.075)				(0.078)	(0.096)	(0.097)
IBES Analyst Disp		0.164**			0.090	0.115	0.106
		(0.065)			(0.067)	(0.126)	(0.149)
Blue-Chip Disp			0.203***			0.136*	0.133*
			(0.062)			(0.078)	(0.081)
SPF Professional Disp				0.172**			0.021
				(0.068)			(0.168)
Constant	−4.563***	−3.718***	−2.831***	−3.404***	−4.995***	−6.216***	−6.134***
	(0.739)	(0.760)	(0.836)	(0.699)	(0.809)	(1.484)	(1.619)
Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.564	0.545	0.559	0.545	0.565	0.587	0.586
N	407	407	330	407	407	330	330

Table 5: Mutual Fund flow and Belief Dispersion

The table reports mutual fund flow's responses to the dispersion among SCA respondents' beliefs. Independent variables also include monthly dummies. Numbers in parentheses are Newey-West adjusted standard errors. ***, ** and * correspond to significance levels at 99%, 95% and 90% correspondingly. Dependent variable *Turnover* is measured monthly and is quoted in percentage points. It is also trend adjusted using cubic detrending.

	Model 1	Model 1.b	Model 1.c	Model 1.d	Model 2	Model 3	Model 4
Lag Fund Flow	0.531***	0.547***	0.522***	0.536***	0.531***	0.504***	0.492***
	(0.043)	(0.043)	(0.044)	(0.043)	(0.042)	(0.044)	(0.044)
Mean Expectation	0.006*	−0.001	0.001	−0.000	0.004	0.006*	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
S&P Return	0.009	0.034	0.029	0.040	0.040	0.031	0.037
	(0.056)	(0.058)	(0.058)	(0.057)	(0.057)	(0.057)	(0.057)
S&P Volatility	1.986***	2.170***	2.237***	2.317***	2.207***	2.274***	2.439***
	(0.362)	(0.372)	(0.374)	(0.382)	(0.368)	(0.370)	(0.378)
Stock liquidity	−0.453	−0.442	−0.418	−0.386	−0.381	−0.350	−0.276
	(0.443)	(0.447)	(0.446)	(0.446)	(0.440)	(0.439)	(0.438)
Post 2007	−0.113	0.012	0.044	−0.003	−0.093	−0.074	−0.122
	(0.097)	(0.091)	(0.095)	(0.089)	(0.096)	(0.100)	(0.103)
SCA Household Disp	0.060**				0.079***	0.086***	0.095***
	(0.024)				(0.025)	(0.026)	(0.026)
IBES Analyst Disp		−0.036			−0.060**	−0.029	0.013
		(0.024)			(0.025)	(0.033)	(0.040)
Blue-Chip Disp			−0.032**			−0.029	−0.020
			(0.016)			(0.021)	(0.022)
SPF Professional Disp				−0.062**			−0.084*
				(0.028)			(0.045)
Constant	1.509***	2.054***	1.753***	1.792***	1.948***	1.666***	1.335***
	(0.274)	(0.328)	(0.258)	(0.257)	(0.327)	(0.377)	(0.414)
Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Square	0.597	0.593	0.592	0.596	0.604	0.604	0.607
N	335	335	330	335	335	330	330

Table 6: Robustness

The table reports Independent variables also include monthly dummies. Numbers in parentheses are Newey-West adjusted standard errors. ***, ** and * correspond to significance levels at 99%, 95% and 90% correspondingly. Dependent variable *Turnover* is measured monthly and is quoted in percentage points. It is also trend adjusted using cubic detrending.

Subgroups	Model 1	Model 2	Model 3	Model 4
Baseline	0.359***	0.332***	0.417***	0.415***
	(0.105)	(0.109)	(0.134)	(0.134)
Variation in dependent variable				
Excluding NASDAQ	0.274**	0.247**	0.326**	0.332**
	(0.109)	(0.115)	(0.145)	(0.146)
Linear Detrending	0.338***	0.343***	0.291**	0.256**
	(0.104)	(0.111)	(0.121)	(0.119)
Quadratic Detrending	0.351***	0.293***	0.361***	0.353***
	(0.103)	(0.103)	(0.129)	(0.129)
Baker-Stein Detrending	0.301***	0.314***	0.404***	0.420***
	(0.105)	(0.114)	(0.143)	(0.144)
Variation in dispersion measure calculation				
Standard Deviation	0.122	0.082	0.259**	0.253**
	(0.088)	(0.087)	(0.116)	(0.116)
1 1.5 1	0.295***	0.266***	0.346***	0.343***
	(0.096)	(0.099)	(0.127)	(0.127)
1 1 1	0.261***	0.228**	0.270*	0.264*
	(0.092)	(0.098)	(0.143)	(0.144)
Ownership Weighted	0.494***	0.540***	0.625***	0.637***
	(0.132)	(0.139)	(0.185)	(0.186)

Table 7: Turnovers and Belief Dispersion, by Market Cap Tercile

The table reports turnovers' responses to the dispersion among SCA respondents' beliefs. Dispersion of PEXP, BUS5, BEXP, RATEX and UNEMP are measured using the weighted negative Herfindahl index ($WNHI$). PCA is the first principle component of the dispersion of the other five variables. Independent variables also include monthly dummies. Numbers in parentheses are Newey-West adjusted standard errors. ***, ** and * correspond to significance levels at 99%, 95% and 90% correspondingly. Dependent variable $Turnover$ is measured monthly and is quoted in percentage points. It is also trend adjusted using cubic detrending.

	All	Large Cap	Medium Cap	Small Cap
L.Detrended Turnover	0.420***	0.449***	0.611***	0.707***
	(0.048)	(0.047)	(0.041)	(0.034)
Mean Expectation	0.054***	0.040**	0.038***	0.039***
	(0.014)	(0.017)	(0.013)	(0.012)
S&P Return	0.320	0.108	0.910***	1.161***
	(0.212)	(0.275)	(0.233)	(0.220)
S&P Volatility	7.675***	10.774***	0.256	−0.778
	(1.396)	(1.832)	(1.364)	(1.264)
Stock liquidity	−3.314**	−4.331**	−3.093*	0.163
	(1.608)	(2.078)	(1.816)	(1.703)
Post 2007	−1.076***	−2.319***	−1.223***	−0.366
	(0.393)	(0.536)	(0.397)	(0.338)
SCA Household Disp	0.415***	0.404***	0.145	0.098
	(0.097)	(0.125)	(0.099)	(0.088)
IBES Analyst Disp	0.106	0.138	0.240	0.185
	(0.149)	(0.195)	(0.148)	(0.130)
Blue-Chip Disp	0.133*	0.200*	−0.060	−0.180**
	(0.081)	(0.105)	(0.081)	(0.074)
SPF Professional Disp	0.021	0.237	−0.047	0.098
	(0.168)	(0.221)	(0.166)	(0.149)
Constant	−6.134***	−4.446**	−4.093***	−3.437**
	(1.619)	(2.053)	(1.560)	(1.398)
Month Effects	Yes	Yes	Yes	Yes
Adj. R-Square	0.586	0.705	0.482	0.615
N	330	330	330	330

Table 8: Turnover Sensitivities To Belief Dispersion Among Demographic Groups, unchanged

The table reports turnovers' responses to belief dispersion among SCA demographic sub-samples. Dispersion measures are constructed and regressions are run separately for each demographic group. Each cell reports the β coefficient in Equation (4). Independent variables also include monthly dummies. Numbers in parentheses are Newey-West adjusted standard errors. ***, ** and * correspond to significance levels at 99%, 95% and 90% correspondingly. Turnovers are quoted in percentage points and trend-adjusted.

Subgroups	Model 1	Model 2	Model 3	Model 4
by age				
Age $<$ 35	0.171*	0.147	0.164	0.166
	(0.098)	(0.099)	(0.112)	(0.113)
Age $\geq$ 35	0.335***	0.307***	0.402***	0.405***
	(0.095)	(0.099)	(0.123)	(0.124)
by education				
Below high school	0.115	0.095	0.091	0.089
	(0.084)	(0.081)	(0.095)	(0.095)
High school graduates	0.387***	0.361***	0.451***	0.452***
	(0.108)	(0.113)	(0.140)	(0.141)
by race				
Black	0.191***	0.180**	0.180*	0.177*
	(0.072)	(0.070)	(0.092)	(0.092)
White	0.337***	0.305***	0.384***	0.382***
	(0.102)	(0.108)	(0.132)	(0.132)
by income				
Lowest income quintile	0.142*	0.124	0.190*	0.185*
	(0.084)	(0.082)	(0.107)	(0.108)
Highest income quintile	0.260**	0.226*	0.252*	0.246*
	(0.111)	(0.120)	(0.140)	(0.140)
by likelyhood to hold stocks				
Less likely to hold stocks	0.190**	0.173**	0.223**	0.219**
	(0.084)	(0.082)	(0.104)	(0.105)
More likely to hold stocks	0.399***	0.372***	0.438***	0.439***
	(0.107)	(0.115)	(0.138)	(0.138)

Table 9: Turnovers and Dispersion of Belief Changes in the SCA sample

The table reports turnovers' responses to dispersion of belief changes among SCA respondents. Independent variables also include monthly dummies. Numbers in parentheses are Newey-West adjusted standard errors. ***, ** and * correspond to significance levels at 99%, 95% and 90% correspondingly. Turnover is also trend-adjusted.

	Turnover	Turnover 6 month
Belief Change	0.167∗∗∗	1.135∗∗∗
	(0.062)	(0.359)
L.Detrended Turnover	0.509∗∗∗	
	(0.041)	
L6.Detrended Turnover		0.520∗∗∗
		(0.055)
Mean Expectation	0.016∗∗	0.014∗
	(0.007)	(0.008)
S&P Return	0.388∗∗	5.386∗∗
	(0.174)	(2.646)
S&P Volatility	7.698∗∗∗	11.702∗∗∗
	(1.244)	(1.974)
Stock liquidity	−3.456∗∗	−5.085
	(1.490)	(3.719)
Post 2007	−0.200	1.161
	(0.278)	(1.859)
Constant	−3.189∗∗∗	−28.088∗∗∗
	(0.664)	(5.102)
Month Effects	Yes	Yes
Adj. R-Square	0.546	0.657
N	401	396

Figure 1: Monthly Belief Dispersion from Household Surveys

This figure plots time series of dispersion of beliefs on five expectation variables in SCA. The five expectation variables are unemployment, interest rates, short-term business conditions (BEXP), personal financial conditions (PEXP) and long-term business conditions (BUS5). The last panel plots the first principle component of the five dispersion series. Belief dispersion are measured using weighted negative Herfindahl index (WNHI) described in Equation (2). Larger values indicate higher dispersion. Shaded areas are NBER recession periods.

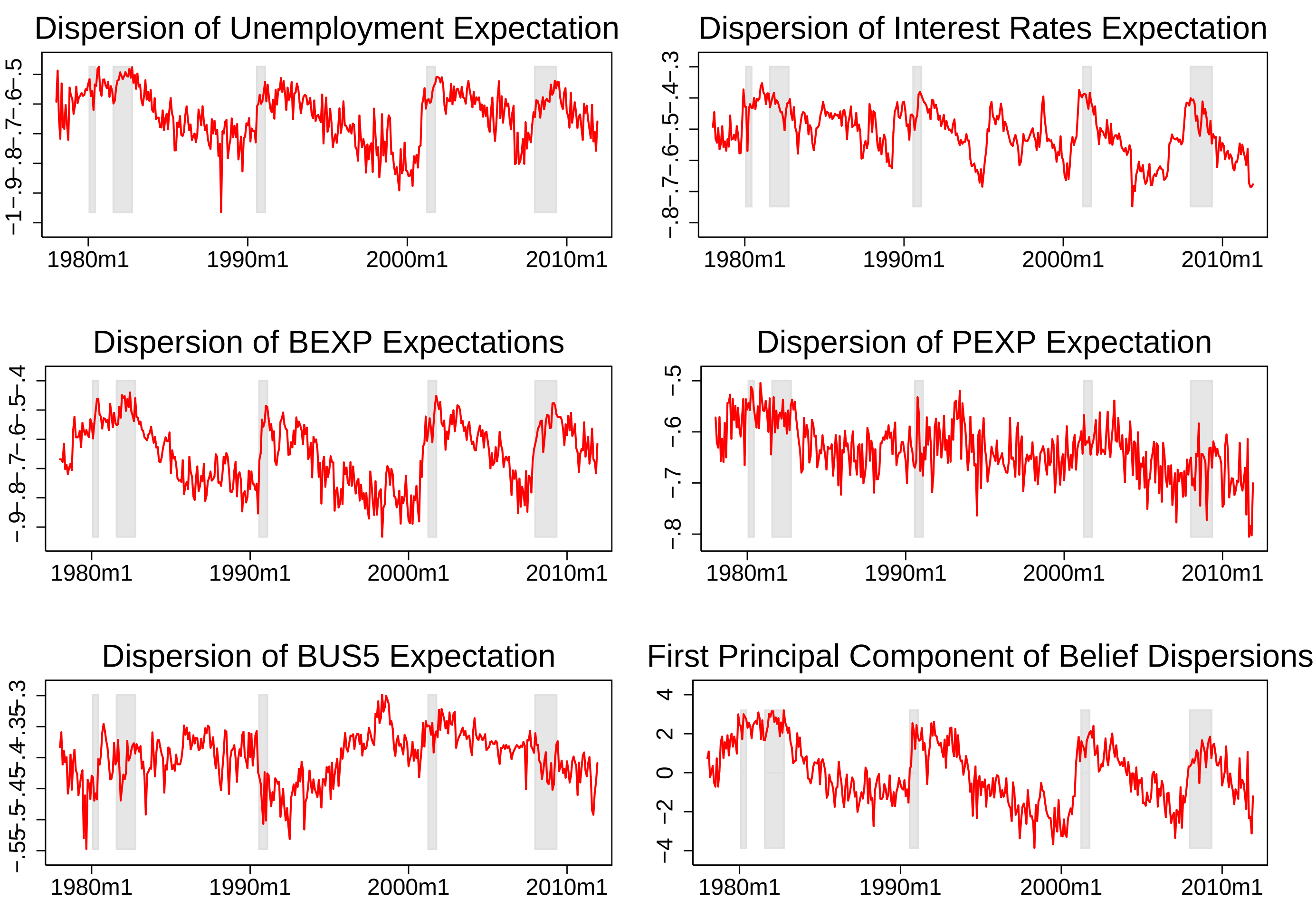

Figure 2: Comparison of Household Belief Dispersion Measure to Professional Belief Dispersion Measures

This figure compares household belief dispersion from the SCA forecasts to the belief dispersions of professional forecasters in the SPF forecasts, IBES analyst forecasts and Blue Chip forecasts. Data frequency is monthly. The date range is from Jan. 1978 to Dec. 2011 for all time series except the Blue Chip time series, which is only available from Jul. 1984. Shaded areas correspond to NBER recessions.

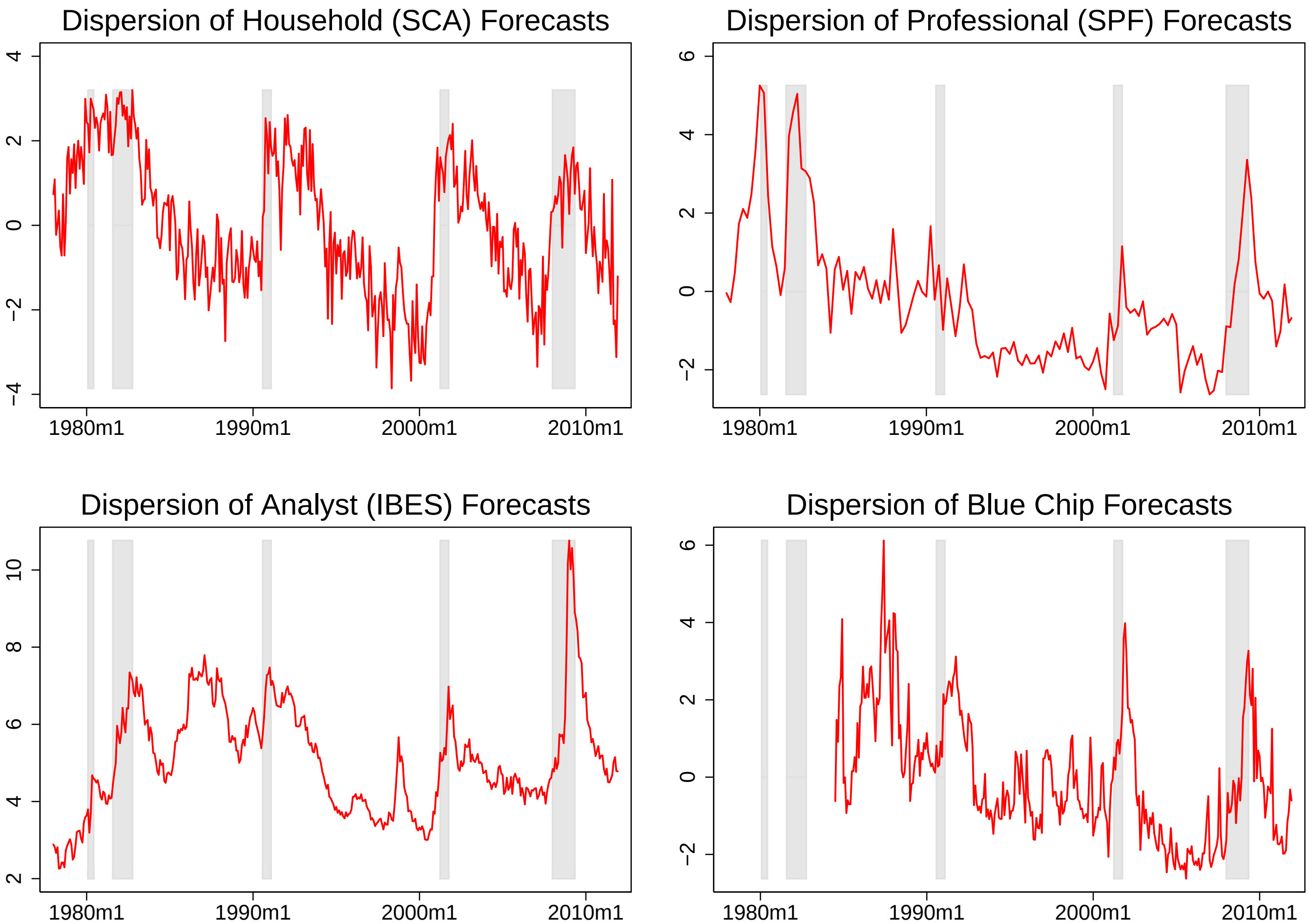

Figure 3: Stock Market Turnover and Aggregate Flows to Stock Market Mutual Funds

This figure plots monthly time series of our proxies for household trading activities in the US stock market. The top panel shows the turnover rates, middle panel shows the turnover rates after cubic-detrending and the bottom panel shows the aggregate flows to stock market mutual funds. All three variables are in fractions. Turnover rates is defined as the combined number of shares traded in NYSE, AMEX and NASDAQ in a given month divided by the average total number of shares outstanding during the same month. Mutual fund flow is defined as total absolute outflow plus total absolute inflow as a fraction of aggregate fund size in the same month. The date range is from 1978 to 2011 for turnover rates and from xx to 2011 for total fund flow variable. Shaded areas correspond to NBER recessions.

Figure 4: Time Series of Main Controls

This figure plots monthly time series of three main control variables in our baseline model of Equation (4). The top panel is the return of S & P 500 index (annualized). The middle panel is the aggregate level of stock market liquidity as in Pastor and Stambaugh (JPE 2003). The bottom panel is the volatility of S&P index (annualized). The date range is from 1978 to 2011. Shaded areas correspond to NBER recessions.