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Abstract

Most studies on disagreement focus on cross-sectional asset returns and well-recognized disagreement measures generally cannot predict the stock market with a horizon less than 12 months. This paper proposes three aggregate disagreement indexes by aggregating information across 20 disagreement measures. We show that disagreement measures collectively have a common component that has significant power in predicting the stock market both in- and out-of-sample. Consistent with the theory developed by Atmaz and Basak (2017), the indexes asymmetrically forecast the market with greater power in high sentiment periods. Moreover, the indexes negatively predict economic activities, and positively predict market volatility, illiquidity, and trading volume.

Keywords: Disagreement; Market risk premium; Predictability; Information aggregation; PLS

JEL Classification: G12, G14

1 Introduction

Researchers in economics and finance have long been interested in studying the effects of disagreement or heterogeneity in beliefs. In economics, disagreement has been offered as an explanation for why monetary policy shocks can have real and persistent effects on output growth (Woodford, 2003; Mackowiak and Wiederholt, 2009; Bachmann, Elstner, and Sims, 2013). In finance, disagreement has been linked to stock returns, volatility, liquidity, trading volume, and Treasury yield curve (Diether, Malloy, and Scherbina, 2002; Chen, Hong, and Stein, 2002; Sadka and Scherbina, 2007; Berkman, Dimitrov, Jain, Koch, and Tice, 2009; Hong and Sraer, 2016; Hong, Sraer, and Yu, 2017). Due to its wide impacts, Hong and Stein (2007) conclude that disagreement represents "the best horse" for behavioral finance to obtain as much insights as classical asset pricing theories.

Unfortunately, disagreement is unobservable. There are numerous proxies in the literature. For example, professional forecast dispersions (Li, 2016), household forecast dispersions (Li and Li, 2015), analyst forecast dispersions (Diether, Malloy, and Scherbina, 2002; Hong and Sraer, 2016), unexplained trading volume (Garfinkel and Sokobin, 2006; Garfinkel, 2009), and stock idiosyncratic volatility (Boehme, Danielsen, and Sorescu, 2006) are some of the major disagreement measures to date. However, there is a lack of research to understand them collectively.

This paper examines whether disagreements are agreeable by exploring the true disagreement implied by all the proxies. If extant measures do measure disagreement, they should display commonality and have a common factor. To aggregate information across 20 measures, we propose three aggregate disagreement indexes, with equal-weighting (EW), principal component analysis (PCA), and partial least squares (PLS) approaches, respectively. Empirically, we show that these three indexes significantly improve the forecasting power. At a one-month horizon, the EW and PCA indexes significantly predict the market in-sample, and the PLS index has significant in- and out-of-sample performance, with an in-sample R^2 of 2.59% and an out-of-sample R^2_{OS} of 1.94%. In contrast, none of the proxies can deliver significant out-of-sample predictability when used individually. At the 12-month horizon, the R^2 and R^2_{OS} of the PLS index are 18.53% and 14.32%, outperforming the up-to-date most powerful predictor, aggregate short interest in Rapach, Ringgenberg, and Zhou (2016), whose values are 12.89% and 13.24%, respectively.

We attribute the forecasting power of disagreement to its ability in predicting future macroeconomic activities. According to Atmaz and Basak (2017), high disagreement generally leads to optimism and decreases investor risk aversion, thereby giving rise to over investments and dampening future activities. Also, high disagreement is related to high economic uncertainty that leads firms to behave cautiously and pause hiring and investment, thereby a drop in future economic activities. With a bunch of macroeconomic indicators, we find that disagreement negatively predicts future industrial production, consumption, and investment, and positively predicts unemployment.

The forecasting power of the disagreement indexes is asymmetric and concentrates in high sentiment periods. For example, the R^2 and R^2_{OS} of the PLS index are 4.74% and 3.53% in high sentiment periods, but they are 0.08% and -0.22% in low sentiment periods. This evidence is consistent with the prediction in Atmaz and Basak (2017) who propose a model to reconcile the inconsistent relation between disagreement and asset returns (Miller, 1977; Diether, Malloy, and Scherbina, 2002; Hong and Stein, 2003; Anderson, Ghysels, and Juergens, 2005; Banerjee and Kremer, 2010; Banerjee, 2011; Yu, 2011; Carlin, Longstaff, and Matoba, 2014). Specifically, disagreement has two opposite effects on stock returns. The first is positive as disagreement represents extra uncertainty, and risk averse investors demand a higher expected return when disagreement is higher. The second effect is negative as high disagreement also amplifies optimism and pushes up the stock price higher than its fundamental value, leading to a lower mean return in the near future. As the stock market goes up more often, investors' view is relatively optimistic, and as such, the second effect is more likely to dominate the first effect, especially in high sentiment periods. With a state-dependent regression, we find that the slope is negative and significant in high sentiment periods, but it is insignificant in low sentiment periods.

There is a large amount of literature exploring the relationship between disagreement and stock volatility, liquidity, and trading volume. However, these papers mainly focus on individual stocks and the contemporaneous relationship. We extend it to the market level and show that, consistent with the theoretical model of Atmaz and Basak (2017), the indexes can positively predict future market volatility, illiquidity, and trading volume. Cross-sectionally, the forecasting power of disagreement is stronger for stocks with low institutional ownership, high beta, and high idiosyncratic volatility.

In robustness tests, we find that the disagreement indexes continue to predict the market when controlling for 14 return predictors and eight macro uncertainty measures. The forecasting power also exists in the international markets because of comovement in market returns or comovement in investor disagreements.

The rest of the paper is organized as follows. Section 2 considers 20 extant disagreement measures and shows that they fail to predict the stock market at a less than 12-month horizon. Section 3 proposes three aggregate disagreement indexes by aggregating information across individual measures and shows that these indexes significantly improve the forecasting power. Section 4 shows the robustness of the disagreement indexes, which is followed by Section 5 with a brief conclusion.

2 Forecasting Power of Extant Disagreement Measures

At a one to 12-month horizon, we show in this section that most of extant disagreement measures fail to predict the stock market in-sample and none of them can deliver significant performance out-of-sample.

2.1 Individual disagreement measures

We consider 20 disagreement measures, among which, nine are based on professional forecasts on macroeconomic conditions, two based on analyst forecasts, six based on household surveys on macroeconomic conditions, and three based on market information. While these measures start in different time periods, they span from December 1968 to December 2016.

2.1.1 Disagreements based on professional forecasts

The disagreements on professional forecasts on macroeconomic conditions are based on the oldest quarterly Survey of Professional Forecasters (SPF) in the U.S. The survey begins in 1968Q4 and is typically released in the mid-to-late second month of each quarter.[1] However, the accurate release dates before 1990Q2 are missing, and to be conservative, we assume that all surveys are known in the last month of each quarter in our analysis. Also, because most of our analysis focuses on a monthly frequency, we convert the quarterly measures into monthly frequency by assigning the most recent quarterly value to each month. For example, the observation in the first quarter of 2016 is assigned to March, April, and May 2016, respectively.

We consider professional forecasts on six macroeconomic variables, gross domestic production (GDP), industrial production (IP), unemployment (UEP), investment (INV), consumer price index (CPI), and 3-month T-bill rate (TBL). As the forecasts on GDP, IP, and INV include both level and growth rate, we therefore have nine disagreement measures in total. We follow Li (2016) and define disagreement as the difference between the 75th percentile and 25th percentile of the forecasts.

[1] Three exceptions with delayed releases are 1990Q2, 1996Q3, and 2013Q4, respectively.

2.1.2 Disagreement based on analyst forecasts

Numerous studies have employed analyst forecast dispersion as the measure of investor disagreement. Following Yu (2011) and Hong and Sraer (2016), we adopt the "bottom-up" approach by defining disagreement in month t as

$$D_t^{\mathrm{Yu}} = \frac{\sum_i \mathrm{MKTCAP}_{i,t} \cdot D_{i,t}}{\sum_i \mathrm{MKTCAP}_{i,t}}, \tag{1}$$

and

$$D_t^{\mathrm{HS}} = \frac{\sum_i \beta_{i,t} \cdot D_{i,t}}{\sum_i \beta_{i,t}}, \tag{2}$$

where $D_{i,t}$ is the analyst forecast dispersion on the EPS long-term growth rate (LTG) of firm i, and MKTCAP and $\beta_{i,t}$ are firm i's market cap and market beta. As explained in Yu (2011), the long-term forecast features prominently in valuation models and is less affected by a firm's earnings guidance than short-term forecast. We regress the last 12-month daily returns on contemporaneous and one to five lagged excess market returns, and use the sum of slopes as the estimate of β.

2.1.3 Disagreement based on household forecasts

Empirical studies often focus on how the trading of securities is affected by disagreement among professional analysts, and seldom explore the disagreement effect of household investors on the broad stock market. Indeed, household investors generally own about 60% of outstanding equities in the U.S. (about 40% direct holding and additional 20% indirect holding through mutual funds),[2] and their opinions should play an important role as institutional investors. Li and Li (2015) show that even controlling for the professional-based disagreement measures, the effect of household disagreement remains significant, and even dominates the professional disagreement.

We construct household disagreement from the Michigan University Survey of Consumers (SCA). The SCA starts conducting monthly surveys from at least 500 consumers in January 1978, and the accurate release date is available after January 1991. In each survey, the SCA collects answers for 50 core questions that are generally related to consumers' opinions on current economic conditions and their expectations about future economic conditions. In this paper, we construct our disagreement measures from six questions. The first question is about consumers' realized opinions on current personal financial condition compared

[2] Flow of Funds Accounts published by the Federal Reserve Board.

with that of one year ago, and the rest five are about consumers' expectations about the following year, consisting of expected personal financial condition, business condition, unemployment condition, interest rate condition, and vehicle purchase condition.

For each question, the surveyed consumers can reply in three categories, better (good), same (depends), and worse (bad). In a consistent way, we rename the categories as positive, neutral, and negative, respectively, and define the proportion of each category as P_{positive}, P_{neutral}, and P_{negative}. We follow Li and Li (2015) and define the disagreement as the weighted negative Herfindahl index as:

$$D = -\sum w_i P_i^2, \quad i = \text{positive, neutral, negative,} \tag{3}$$

where w_i is the weight of each category as $w_{\text{positive}} = 1$, $w_{\text{neutral}} = 2$, and $w_{\text{negative}} = 1$. We assign a higher weight to the neutral category to avoid the unfavourable feature of evenly weighted Herfindahl index. For example, if 50% consumers choose positive and 50% choose negative, the weighted Herfindahl index is the same as 50% positive and 50% neutral. However, the first case is obviously more dispersed than the second case.

2.1.4 Disagreement based on unexplained stock trading volume

Ajinkya, Atiase, and Gift (1991) find that high trading volume is associated with the increase in analyst forecast dispersion, suggesting that trading volume may measure investor disagreement. We follow Garfinkel (2009) and construct a disagreement measure as the standardized unexplained volume. Specifically, we obtain the monthly aggregate trading volume data of NYSE from Pinnacle, and define volume as the log volume minus its previous 60 month moving average. Then, we run the following time series regression with the past 60 month data at the end of each month as

$$\text{Volume}_t = \alpha + \beta_1 \cdot R_t^+ + \beta_2 \cdot R_t^- + \varepsilon_t, \tag{4}$$

and use the last value of the residuals as the estimate of unexpected volume. In (4), the plus and minus signs in the superscript mean that the market returns are positive or negative, and capture the empirical fact that positive and negative returns generate different levels of trading volume. Thus, investor disagreement can be defined by the standardized unexplained volume:

$$D_t^{\mathrm{SUV}} = \frac{\varepsilon_t}{S_t}, \tag{5}$$

where S_t is the standard deviation of the regression residuals.

2.1.5 Disagreement based on idiosyncratic volatility

Inspired by theoretical studies such as Shalen (1993) and Harris and Raviv (1993) that construct a close connection between belief dispersion and volatility, Boehme, Danielsen, and Sorescu (2006) propose the idiosyncratic volatility as a disagreement measure as the firm level. We extend this measure to the market level. Specifically, following Ang, Hodrick, Xing, and Zhang (2006), we regress daily stock returns on the Fama and French (1993) three factors with a rolling window of 250 days with all stocks on NYSE, NASDAQ, and AMEX, and estimate the firm level idiosyncratic volatility at the end of each month. We then define investor disagreement as the value-weighted idiosyncratic volatility.

2.1.6 Disagreement based on option open interest

Disagreement can be also constructed from option market. Investors who hold call options have a bullish view, whereas investors who hold put options have a bearish view. Following Ge, Lin, and Pearson (2016), we define disagreement as one minus the scaled difference between OEX call and put open interests:

$$D_t^{\mathrm{OID}} = 1 - \frac{|\mathrm{COI}_t - \mathrm{POI}_t|}{|\mathrm{COI}_t + \mathrm{POI}_t|}, \tag{6}$$

where COI_t is the call option open interest and POI_t is the put option open interest. The scaled call and put option open interest difference $|\mathrm{COI}_t - \mathrm{POI}_t|/|\mathrm{COI}_t + \mathrm{POI}_t|$ ranges from zero to one. The intuition is that when disagreement is low, investors' beliefs polarize to bullish or bearish. The difference between call and put option open interest diverges, and scaled difference approaches one. One minus the scaled difference is accordingly low. When disagreement is high, the forces between optimists and pessimists are tight. Call and put option open interests should be commeasurable. The scaled difference between call and put option open interest approaches zero. Hence, one minus the scaled difference is accordingly high.

2.2 Summary statistics

Panel A of Table 1 presents summary statistics of the 20 disagreement measures, including the sample period, mean, standard deviation, minimum, maximum, skewness, and kurtosis. It is apparent that the scale across disagreement measures varies dramatically due to the feature of fundamental variables. For instance, the mean of disagreement on GDP is 61.42 billions, while the mean of disagreement on 3-month T-bill rate is only 0.47%. Thus, to make them comparable and to avoid looking-forward bias, we standardize each disagreement measure in month t by its last 10-year mean and standard deviation. To remove possible macroeconomic information, we regress each individual disagreement measure on the six economic variables in Baker and Wurgler (2006), which consist of the growth of industrial production, the growth of durable consumption, the growth of of nondurable consumption, the growth of service consumption, the growth of employment, and a dummy variable for NBER dated recessions.

Panel B of Table 1 presents pairwise correlations between disagreement measures. Most of the individual disagreement measures are positively correlated, with several exceptions of negligible negative values. In particular, macro disagreement measures are all positively correlated, and they are also positively correlated with the two analyst forecast dispersions. Trading volume- and option open interest-based disagreement measures have little correlations with other measures. In general, this panel indicates that extant disagreement measures capture both the common and different aspects of the economy, and it is unlikely complete to explore the aggregate effect of disagreement on the stock market by using a specific one.

2.3 Forecasting power of extant disagreement measures

We explore the forecasting power of disagreement on the stock market with the following predictive regression:

$$R_{t+1} = \alpha + \beta D_t + \varepsilon_{t+1}, \tag{7}$$

where R_{t+1} is the log excess return of the S&P 500 index in month $t+1$ and D_t is one of the 20 individual disagreement measures. When the forecast horizon is h months, we denote the dependent variable as $R_{t,t+h} = \frac{1}{h}\sum_{j=1}^{h} R_{t+j}$.

The forecasting power is based on the regression slope β or the R^2 statistic. If β is significantly different from zero or the R^2 is significantly larger than zero, we conclude that D_t is a predictor of the market return. The out-of-sample forecast of next period's expected market return is recursively computed as

$$\hat{R}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t D_t, \tag{8}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the ordinary least squares estimates of α and β based on data from the start of the available sample through t. The in-sample forecast is computed the same as above except that $\hat{\alpha}_t$ and $\hat{\beta}_t$ are replaced by those estimated by using the entire sample.

We use Campbell and Thompson (2008) out-of-sample R^2 statistic as the out-of-sample performance evaluation criterion, and define it as:

$$R^2_{OS} = 1 - \frac{\sum_{t=K}^{T}(R_t - \hat{R}_t)^2}{\sum_{t=K}^{T}(R_t - \bar{R}_t)^2}, \tag{9}$$

where $K-1$ is the size for in-sample parameter training and $T-K+1$ is the number of out-of-sample observations. $\hat{R}_t$ is the excess return forecast with (8), and $\bar{R}_t$ is the historical mean forecast, both of which are estimated using data up to month $t-1$. If D_t is viable, R^2_{OS} will be positive and its mean-squared forecast error (hereafter MSFE) is lower than the MSFE with the forecast based on the historical average return. Campbell and Thompson (2008) show that a monthly R^2_{OS} of 0.5% can generate significant economic value. The null hypothesis of interest is therefore $R^2_{OS} \leq 0$ against the alternative hypothesis that $R^2_{OS} > 0$. We test this hypothesis by using the Clark and West (2007) MSFE-adjusted statistic.

Panel A of Table 2 presents the regression slope β, Newey-West t-statistic, in-sample R^2, and out-of-sample R^2_{OS}. Throughout this paper, the out-of-sample period is from February 1991 to December 2016 as the accurate release date of household disagreement measures is available as of January 1991. Consistent with Miller (1977), 19 out of 20 disagreement measures have a negative forecasting sign, among which, however, only the disagreement on the 3-month T-bill rate forecasts has significant forecasting power, with a t-statistic of -2.57. The out-of-sample performance confirms the in-sample result, and all of the R^2_{OS}s are negative, suggesting that the forecasting with individual disagreement measures underperforms the historical mean forecast.

Panels B and C of Table 2 present similar results as Panel A when the forecasting horizon is extended to 3 months or 12 months. The in-sample regression slopes are seldom significant and the R^2_{OS} are all negative. Consistent with Yu (2011) that the value-weighted analyst forecast dispersion exhibits insignificant power at a one-month horizon but significant power at a 12-month horizon. However, Yu (2011) does not show out-of-sample performance and our results tell that the analyst forecast dispersion cannot generate meaningful real time forecasting.

Overall, Table 2 suggests that while all of the extant disagreement measures may have cross-sectional forecasting power, they are unable to predict the aggregate market in general, especially for real time forecasting.

3 Aggregate disagreement indexes

In this section, we construct three aggregate disagreement indexes with three different approaches and show that they can significantly improve the stock market return predictability.

3.1 Methodology

To aggregate information across the 20 individual disagreement measures, we use three approaches, the simple equal-weighting (EW) approach, PCA approach, and PLS approach. As a result, we have three aggregate disagreement indexes, D^{EW}, D^{PCA}, and D^{PLS}, corresponding to the three approaches accordingly.

Equal-weighting may be the simplest approach in aggregating information. At the end of each month, we normalize each of the 20 disagreement measures with mean zero and variance one, and define the disagreement index D^{EW} as the cross-sectional mean. This approach can efficiently reduce the idiosyncratic measurement and observation errors in the individual disagreement measures.

The PCA approach is to extract the first principal component as the aggregate disagreement index, which maximally represents the total variations of the 20 disagreement measures. This approach has been widely used in finance, such as Buraschi and Whelan (2012) who use the PCA approach to construct their disagreement index and Baker and Wurgler (2006) who construct the investor sentiment index as the first principal component of six individual sentiment proxies. Because the individual disagreement measures have different starting points, we employ the probabilistic principal component method as Stock and Watson (2002) to solve the missing value issue[3].

As the goal of this paper is to construct a disagreement index to predict the stock market, the EW

[3] We use the embedded Matlab package ppca.m to run probabilistic principal component.

and PCA approaches may fail to do a fair job if the individual disagreement measures have common measurement or observation errors, in that these two approaches can capture the maximum common variations but cannot tease out the common component that is unrelated to expected stock returns. As a result, we employ the PLS approach, which has been introduced to finance by Kelly and Pruitt (2013) for return predictability.

The PLS approach consists of three steps. In the first step, we run a time-series regression of each individual disagreement measure on the realized subsequent market return (as a proxy of expected return) with full sample as:

$$D_{t-1}^{k} = \pi_{k,0} + \pi_k R_t + u_{k,t-1}, \quad k = \text{GDP}, \ldots, \text{ OID}, \tag{10}$$

where π_k capture the sensitivity of each disagreement proxy D_{t-1}^{k} to expected market return. In the second step, we run a cross-sectional regression of D_t^k on $\hat{\pi}_k$ at the end of each month as:

$$D_t^k = a_t + D_t^{\text{PLS}} \hat{\pi}_k + v_{k,t}, \tag{11}$$

where the regression slope D_t^{PLS} is the PLS disagreement index in month t. In the last and third step, to predict R_{t+1}, we run the following predictive regression as:

$$R_{t+1} = \alpha + \beta D_t^{\text{PLS}} + \varepsilon_{t+1}. \tag{12}$$

The above three steps are for in-sample analysis. For out-of-sample forecasting, the standard approach is to repeat the three steps by truncating the observations that are not know at month t. Specifically, consider a forecast for return R_{t+1} that is realized at month $t+1$. A properly constructed forecast can only use information known through month t. In the first step, the latest return that can be used on the right-hand side is R_t and the last observation of disagreement on the left-hand side is therefore D_{t-1}^k. In the second step, the cross-sectional regressions are run for months 1 through t. In the last step, the latest return on the left-hand side entering the predictive regression is R_t and the forecast for R_{t+1} is $\hat{\alpha}_t + \hat{\beta}_t D_t^{\text{PLS}}$, where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the estimates using information up to month t. In summary, for out-of-sample forecasting, all inputs to the forecast are constructed using data that are observed no later than month t.

To iron out extreme outliers, we smooth the three disagreement indexes with their six-month moving average values and plot their time series in Figure 1. There are two interesting observations. First, aggregate disagreement can be high in bad times, such as the recessions of 1981 to 1982 and 2007 to 2008, and in good times, such as the dot-com boom of the late 1990s. This evidence is consistent with the disagreement on analyst forecasts in Hong and Sraer (2016) and consistent with the theoretical prediction in Atmaz and Basak (2017). Second, while D^{EW}, D^{PCA}, and D^{PLS} are constructed differently, they are highly correlated. The correlation of D^{PLS} with D^{EW} is 0.64 and with D^{PCA} is 0.45, and it is 0.83 between D^{EW} and D^{PCA}. This fact implies that individual disagreement measures do contain a common component that is related to expected stock returns.

3.2 Forecasting the market return

Panel A of Table 3 reports the results of forecasting market return with the three aggregate disagreement indexes, which reveals a different pattern with Table 2. At the one-month horizon, a one-standard deviation increase in disagreement leads to a 0.62% decrease in next month expected return with D^{EW} ($t = -3.09$), a 0.35% decrease with D^{PCA} ($t = -2.02$), and a 0.83% decrease in D^{PLS} ($t = -3.69$). When turning to out-of-sample forecasting, the R^2_{OS}s are insignificant with D^{EW} and D^{PCA} (0.13% and -0.24%), but it is 1.94% with D^{PLS} and significant at the 5% level. This result suggests that disagreement does predict the stock market in- and out-of-sample if we aggregate information across individual disagreement measures in an efficient way.

Panels B and C of Table 3 report the cases when the forecasting horizons are three and 12 months, respectively. The in-sample results are significant, and moreover, the D^{EW} also has significant R^2_{OS}s, in addition to D^{PLS}. At the 12-month horizon, the R^2 and R^2_{OS} with D^{PLS} are 18.53% and 14.32%, which even outperform the up-to-date most powerful predictor, aggregate short interest in Rapach, Ringgenberg, and Zhou (2016), whose corresponding values are 12.89% and 13.24%, respectively.

Why does the PLS disagreement index have better performance? One possible reason is that while both the EW and PCA approaches can efficiently reduce the idiosyncratic measurement and observation errors in the individual disagreement measures, they fail to tease out the common errors that are unrelated to expected stock returns. In contrast, as a target driven approach, the PLS approach aggregates information that is relevant to future stock returns and undoubtedly has higher forecasting power. To support this inference, we show that the PLS index puts more weights on those disagreement measures that have higher forecasting power.

Table 4 reports the weights of individual disagreement measures in constructing the three aggregate disagreement indexes. To have a sensible comparison, we focus on the balanced period of 1984:02–2016:12 where all measures have no missing values, and normalize the PCA and PLS weights so that their sum equals one. As a benchmark, the weight of D^{EW} is 0.05 for each individual disagreement measure. The top three weights for D^{PCA} are 10.12%, 9.63%, and 8.11%, corresponding to the beta-weighted and value-weighted analyst forecast dispersions in Hong and Sraer (2016) and in Yu (2011), and professional industrial production forecast dispersion. The top three weights for D^{PLS} are 15.91%, 9.46%, and 8.60%, corresponding to the 3-month T-bill forecast dispersion, the value-weighted analyst forecast dispersion in Yu (2011), and the standardized unexplained volume. Compared with Table 2, it is easy to explain why the D^{PLS} has much better performance. The 3-month T-bill forecast dispersion is the most powerful disagreement measure among the 20 individual proxies, and its in-sample performance is significant at the 1-, 3-, and 12-month horizons. Also, the performance of the value-weighted analyst forecast dispersion in Yu (2011) is significant for the 3- and 12-month horizons in-sample, and the standardized unexplained volume has significant power when the horizon is 12-month. In contrast, the top three weights for D^{PCA} have only one overlap with D^{PLS}, the value-weighted analyst forecast dispersion in Yu (2011), and the other two are not significant in any forecasting horizon, suggesting that the PCA approach may be a good approach for summarizing data, but it is not be good for return predictability.

In summary, extant disagreement measures do have a common component that is able to predict the market. The forecasting power depends on how we aggregate information across individual measures.

3.3 Forecasting macroeconomic activities

According to Atmaz and Basak (2017), high disagreement generally leads to optimism and decreases investor risk aversion. As a result, this optimism will overly boost current economic activities and dampen future activities (Baker, Hollifield, and Osambela, 2016). On the other hand, disagreement is also positively related to economic uncertainty. High disagreement means more disperse forecast errors, which is likely the result of large uncertainty fluctuations. According to Bloom (2009) and Bachmann, Elstner, and Sims (2013), high uncertainty plus nonsmooth adjustment frictions leads firms to behave cautiously and pause hiring and investment, thereby leading to a drop in future economic activities. Therefore, disagreement negatively forecasting the market because it is negatively related to future economic activities.

In this paper we consider eight macroeconomic indicators as the proxy of economic activities, including the Chicago Fed National Activity Index (CFNAI), industrial production growth, real personal consumption growth, unemployment rate, gross private domestic investment, aggregate equity issuance in Baker and Wurgler (2000), total business inventory, and capacity utilization.

The economic variables are adjusted for seasonality and annualized for ease of exposition. Except for gross private domestic investment, all of them are measured at the monthly frequency. To control for the autocorrelations, we run the following regression:

$$y_{t+1} = \alpha + \beta D_t + \sum_{i=1}^{12} \lambda_i y_{t-i+1} + \varepsilon_{t+1}, \tag{13}$$

where y_{t+1} is one of economic indicators, and D_t is one of the three disagreement indexes, $D^{\mathrm{EW}}, D^{\mathrm{PCA}}$, and D^{PLS}. For quarterly investment, we use the following regression:

$$y_{q+1} = \alpha + \beta D_q + \sum_{i=1}^{4} \lambda_i y_{q-i+1} + \varepsilon_{q+1}, \tag{14}$$

where y_{q+1} is the annualized quarterly growth rate of investment.

Table 5 confirms the prediction of Atmaz and Basak (2017) that high disagreement dampens future economic activities.

3.4 Predictability asymmetry of disagreement

One key prediction in Atmaz and Basak (2017) is that disagreement has an asymmetric forecasting pattern in different market states. On the one hard, disagreement represents the extra uncertainty investors face, risk-averse investors demand a higher risk premium. As such, disagreement should positively forecast future stock return. On the other hand, disagreement also amplifies investor optimism and pushes up the stock price further following good news, suggesting that disagreement should negatively predict stock returns. When investor sentiment is low, the first and second effect may offset each other, and the forecasting power of disagreement may be not significant. When investor sentiment is high, however, the view on the stock market is relatively optimistic. Therefore, the second effect dominates and the negative forecasting pattern will be more pronounced.

In this section, we test this prediction in two ways. The first way is to look at the forecasting power in high and low sentiment periods directly. Following Rapach, Strauss, and Zhou (2010) and Henkel, Martin, and Nardari (2011), we compute the in-sample R^2 statistics in high sentiment periods and low sentiment periods as:

$$R_c^2 = 1 - \frac{\sum_{t=1}^{T} I_t^c (\hat{\varepsilon}_t)^2}{\sum_{t=1}^{T} I_t^c (R_t - \bar{R})^2}, \quad c = \text{high, low}, \tag{15}$$

where I_t^{high} (I_t^{low}) is an indicator that takes a value of one when month t is in a high (low) sentiment period and zero otherwise, $\hat{\varepsilon}_t$ is the fitted residual based on the in-sample estimates, $\bar{R}$ is the full-sample mean of R_t, and T is the number of observations for the full sample. Note that, unlike the full-sample R^2 statistic, the R^2_{high} and R^2_{low} statistics can be both positive or negative. Based on the sentiment index of Baker and Wurgler (2006), we define a month as high if the last year's sentiment index is positive, and low otherwise. Similarly, we can also calculate the R^2_{OS} in high and low sentiment periods separately.

Panel A of Table 6 shows that the forecasting power of disagreement concentrates in high sentiment periods. The in-sample R^2s are 2.89%, 1.47%, and 4.74% with the three aggregate disagreement indexes in high sentiment periods, and they are −0.02%, −0.49%, and 0.08% in low sentiment periods. The R^2_{OS}s with D^{EW} and D^{PCA} are not significant in either high or low sentiment periods, but the values with D^{PLS} are significant in high sentiment periods (3.53% in high sentiment periods and −0.22% in low sentiment periods).

The second way to test the forecasting asymmetry of disagreement is to run the following regression:

$$R_{t+1} = \alpha + \beta_1 I_t^{\text{high}} D_t + \beta_2 I_t^{\text{low}} D_t + \varepsilon_{t+1}. \tag{16}$$

Panel B of Table 6 presents the results. As expected, the regression slope in high sentiment periods is −1.02 with a statistic of −3.63, but it is −0.36 with an insignificant t-statistic of −0.94 in low sentiment periods.

In sum, our findings lend direct support to the theoretical prediction of Atmaz and Basak (2017) that the predictability of disagreement on stock returns should concentrate in high sentiment periods.

3.5 Economic value with disagreement prediction

In this section, we examine the economic value of forecasting the stock market with disagreement from the perspective of investing. Following Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011), among others, we explore the annualized certainty equivalent return (CER) gain and monthly Sharpe ratio.

The higher the CER gain and Sharpe ratio, the larger the risk-rewarded return by using disagreement.

Suppose a mean-variance investor invests his wealth between the market portfolio and the one-month T-bill rate. At the start of each month, he allocates a proportion of w_t to the market portfolio to maximize his next month' expected utility

$$U(R_p) = \mathrm{E}(R_p) - \frac{\gamma}{2}\mathrm{Var}(R_p), \tag{17}$$

where R_p is the return of the investor's portfolio, $\mathrm{E}(R_p)$ and $\mathrm{Var}(R_p)$ are the mean and variance of the portfolio return, and γ is the investor's risk aversion.

Let R_{t+1} and $R_{f,t+1}$ be the excess return and T-bill rate. The investor's portfolio return at the end of each month is

$$R_{p,t+1} = w_t R_{t+1} + R_{f,t+1}, \tag{18}$$

where $R_{f,t+1}$ is known at t. With a simple calculation, the optimal portfolio is

$$w_t = \frac{1}{\gamma}\frac{\hat{R}_{t+1}}{\hat{\sigma}^2_{t+1}}, \tag{19}$$

where $\hat{R}_{t+1}$ and $\hat{\sigma}^2_{t+1}$ are the investor's estimates on the mean and variance of the market portfolio based on information up to time t.

The CER of the portfolio is

$$\mathrm{CER} = \hat{\mu}_p - \frac{\gamma}{2}\hat{\sigma}^2_p, \tag{20}$$

where $\hat{\mu}_p$ and $\hat{\sigma}^2_p$ are the mean and variance of the investor's portfolio over the out-of-sample evaluation period. The CER can be interpreted as the compensation to the investor for holding the market portfolio. The difference between the CERs for the investor using the predictive regression based on disagreement and the historical mean as the forecast of the market return is naturally an economic measure of predictability significance.

Table 7 presents the economic value generated by optimally trading on disagreement for the investor with a risk aversion of 3 and 5, respectively. That is, we report the CER difference between the strategy using the disagreement forecast and the strategy using the historical mean forecast of the market return. We annualize the CER by multiplying 1,200 so that the CER difference denotes the percentage gain per year for the investor to use the disagreement index regression forecast instead of the historical mean forecast. Following Campbell and Thompson (2008), we assume that the investor uses a five-year moving window of past monthly returns to estimate the variance of the excess market return, and constraints w_t to lie between -1 and 2 to exclude extreme cases.

The results show that among the three aggregate disagreement indexes, only D^{PLS} generates significant economic value for the investor, which is consistent with Table 3 that only D^{PLS} can generate significant R^2_{OS} at the one-month horizon. In Panel A, when there is no transaction cost, the annualized CER gain by using D^{PLS} is 4.39%, suggesting that investing with the D^{PLS} forecast can generate 4.39% more risk-adjusted return relative to the historical mean forecast. The monthly Sharpe ratio is 0.18, and is much higher than the market Sharpe ratio, 0.10. When there is a transaction cost of 50 basis points, the CER gain by using D^{PLS} is 3.58%, which is still economically sizeable. The corresponding Sharpe ratio is 0.16. Panel B shows similar results when the investor's risk aversion is 5. For example, the CER gain is 3.48% without transaction cost and is 2.84% with a transaction cost of 50 bps.

In summary, we conclude that D^{PLS} is able to deliver considerable economic value for a mean-variance investor.

3.6 Forecasting cross-sectional portfolios

This section explores how disagreement predicts cross-sectional portfolios. Based on the theory of Miller (1977) and Duffie, Garleanu, and Pedersen (2002), the portfolio with firms that are subject to more constraints should be more sensitive to disagreement. Also, the predictability should be more pronounced in high disagreement periods.

D'avolio (2002) shows that institutional ownership is the most important cross-sectional determinant of stock loan supply and argues that short-sale constraints are tighter and the cost of shorting is higher for stocks with low institutional ownership. We follow Nagel (2005) and use institutional ownership as a proxy of short-sale constraint. We form the institutional ownership ratio from Thomson Financial Institutional Holdings (13F) database as of the first quarter of 1980. We sum up all reporting institutional holding for each stock in each quarter as the stock's institutional ownership. Next, we apply the standard portfolio sorting method to construct 10 portfolios at the end of each quarter based on institutional ownership deciles and using valued weighted return as the portfolio return. We denote the lowest (highest) portfolio as decile 1 (10). Also, we define month t as high (low) disagreement period if the D^{PLS} in the month $t-1$ is above (below) its previous 24-month moving average.

Panel A of Figure 2 plot the institutional ownership decile portfolio returns in high and low disagreement periods, and the solid line stands for the difference between average portfolio return between high and low disagreement period. Apparently, in high disagreement periods, the portfolio return show a strong upward pattern from decile 1 to decile 10, suggesting that portfolio with low institutional ownership generates low stock returns. The reason is that stocks with low institutional ownership are harder to short, reflect more views of optimistic investors, and therefore over more likely to be overvalued. In the future, these stocks have predictable low returns.

Another prediction about disagreement is from Hong and Stein (2007), who argue that because of investor disagreement on the market risk premium, high beta portfolios are more likely to be overpriced in high disagreement periods. To test this prediction, we collect beta decile portfolio returns from Ken French webpage and plot their average returns in Panel B of Figure 2. Consistent with Hong and Stein (2007), the high beta portfolio has a lower average return in high disagreement periods, and is more sensitive to disagreement.

Finally, we use the idiosyncratic volatility as a general measure of arbitrage costs in the spirit of Pontiff (2006) and Stambaugh, Yu, and Yuan (2015). As high idiosyncratic volatility portfolio are more speculative and harder to arbitrage, in high disagreement period, the overvaluation should be more apparent. Panel C of Figure 2 displays this pattern. The average return differences between high and low disagreement period are more negative for high idiosyncratic volatility portfolio.

Overall, the disagreement index D^{PLS} does generate consistent evidence as predicted by theoretical studies like Miller (1977) and Hong and Stein (2007).

3.7 Disagreement and Volatility

The theory in Atmaz and Basak (2017) suggests a positive relation between disagreement and stock volatility. This section uses two volatility measures to test this prediction. One is VIX, an ex-ante volatility measure, and the other is the market realized volatility,

$$\text{Realized volatility} = \ln\sqrt{\text{SVAR}}, \tag{21}$$

where SVAR is the sample variance of S&P 500 index return from Welch and Goyal (2008). As volatility is persistent, we run the following regression:

$$y_{t+1} = \alpha + \beta_1 D_t + \beta_2 y_t + \varepsilon_{t+1}, \tag{22}$$

where y_{t+1} is either VIX or realized volatility in month $t+1$.

Table 8 shows that the three disagreement indexes proposed in this paper positively and significantly predict future market volatilities.

3.8 Disagreement and market liquidity

The relation between disagreement and market liquidity is paid less attention than that with volatility. Sadka and Scherbina (2007) find a positive association between disagreement and contemporaneous illiquidity at the firm level. The reason is that overvaluation of high disagreement stocks have higher trading costs, making it more difficult to correct their mispricing. Kruger (2015) proposes a theory to justify this relationship based on information asymmetry.

We use two liquidity proxies to explore their relation with disagreement. The first one is the Amihud (2002) aggregate illiquidity, which equally weights firm level illquidity measures as Chen, Eaton, and Paye (2016). To correct the impact of inflation, the dollar trading volume is adjusted by the CPI index to the December 2016 dollar. To remove the impact of irregular trading, we eliminate observations with daily dollar trading volumes less than $100,000, and winsorize the firm level illiquidity measures at the 5% and 95% percentiles on a monthly basis. The second measure is the Pástor and Stambaugh (2003) aggregate liquidity from Lubos Pástor's website.

Table 9 shows that our disagreement indexes positively predict next month illiquidity and negatively predict next month liquidity.

3.9 Disagreement and trading volume

There is a large amount of literature suggesting a positive relationship between disagreement and trading volumes, such as Ajinkya, Atiase, and Gift (1991), Banerjee (2011), and Atmaz and Basak (2017).

We measure the market trading volume by the log turnover of NYSE, S&P 500 ETF (SPY), or NASDAQ ETF (QQQ), which is defined as the ratio of the number of shares traded to the number of total shares outstanding. As the turnover of the U.S. market exponentially increases over time (Campbell, Grossman, and Wang, 1993; Baker and Wurgler, 2006), we detrend the log turnovers by their five-year moving averages. Then, we run the following regression:

$$\text{Volume}_{t+1} = \alpha + \beta_1 D_t + \beta_2 \text{Volume}_t + \varepsilon_{t+1}. \tag{23}$$

Table 10 presents the results. As expected, trading volume or turnover is sensitive to and can be predicted by disagreement. This finding is also confirmed with household surveys shown in Li and Li (2015).

4 Robustness

We provide three more tests to show that our findings are robust.

4.1 Comparison with economic predictors

Following Welch and Goyal (2008), and Rapach, Ringgenberg, and Zhou (2016), we explore whether the forecasting power of disagreement continues to exist when controlling for existing economic predictors. In so doing, we consider 14 monthly macroeconomic variables in Welch and Goyal (2008), and run the following regression:

$$R_{t+1} = \alpha + \beta D_t + \psi Z_t + \varepsilon_{t+1}, \tag{24}$$

where R_{t+1} is the market excess return, D_t is one of the three disagreement indexes, and Z_t is one of the 14 economic predictors.

Table 11 reports results. In Panel A, we show that over the sample period 1969:12–2016:12, almost all of the economic predictors cannot significantly predict the market, with two exceptions (long-term bond return and term spread). Panels B, C, and D show that controlling economic variables do not reduce the disagreement forecasting power at all. For example, when term spread and disagreement are jointly used as predictors, the regression slope is -0.59 with D^{EW}, -0.33 with D^{PCA}, and -0.81 with D^{PLS}, all of which are significant and are almost the same as that without controlling for term spread as shown in Table 3 (-0.62, -0.35, and -0.83).

In summary, the predictive ability of disagreement remains after controlling for extant economic predictors, suggesting that disagreement captures independent information different with economic fundamentals.

4.2 Comparison with uncertainty

In the literature, disagreement has two alternative interpretations: investor heterogeneity and uncertainty. For example, Anderson, Ghysels, and Juergens (2005) show both theoretically and empirically that heterogeneous beliefs matter for asset pricing and measure the heterogeneity of beliefs (disagreement) by analyst forecast dispersion. In contrast, in Anderson, Ghysels, and Juergens (2009), the same authors interpret analyst forecasting dispersion as a proxy of investor uncertainty. While the alternative explanations can be reconciled by the theory of Atmaz and Basak (2017), it is still empirically interesting to explore whether the disagreement indexes are different with macro uncertainty. To resolve the concern, we employ eight uncertainty measures, including economic uncertainty index (UNC) in Bali, Brown, and Caglayan (2014), treasury implied volatility (TIV) in Choi, Mueller, and Vedolin (2017), economic policy uncertainty (EPU) in Baker, Bloom, and Davis (2016), financial uncertainty (FU), economy uncertainty (EU), and real uncertainty (RU) in Ludvigson, Ma, and Ng (2015), sample variance (SVAR) in Welch and Goyal (2008), and VIX.

We first report the correlations of the disagreement indexes with the eight uncertainty measures in Panel A of Table 12. Consistent with Anderson, Ghysels, and Juergens (2009), disagreement does positively correlate with uncertainty. For example, the correlations between our disagreement indexes and the economic uncertainty index (UNC) in Bali, Brown, and Caglayan (2014) are 0.29, 0.38, and 0.19, and the corresponding values with the financial uncertainty of Ludvigson, Ma, and Ng (2015) are 0.40, 0.54, and 0.26, respectively.

Then, we investigate the forecasting power of disagreement by controlling for macro uncertainty as:

$$R_{t+1} = \alpha + \beta D_t + \psi U_t + \varepsilon_{t+1}, \tag{25}$$

where U_t is one of the eight uncertainty measures. As a benchmark, Panel B of Table 12 shows that extant uncertainty measures cannot significantly predict the market with one exception, financial uncertainty of Ludvigson, Ma, and Ng (2015). Panels C, D, and E consider the three disagreement indexes separately. Collectively, the results suggest that disagreement remains significant in predicting the market while controlling for macro uncertainty.

4.3 Forecasting international markets

Rapach, Strauss, and Zhou (2013) show that the lagged U.S. market return significantly predicts returns in other non-U.S. industrialized countries in- and out-of-sample. So one natural question is whether disagreement that predicts the U.S. market can also predict the international markets.

We consider G10 countries based on the definition of Bank for International Settlements, including Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, and the United Kingdom. We use the monthly returns on Morgan Stanley Capital International (MSCI) index of each country as the equity market performance over 1970:01–2015:12, and run the following regression:

$$R^j_{t+1} = \alpha + \beta D_t + \varepsilon_{t+1}, \tag{26}$$

where R^j_{t+1} is the excess return of country j in month $t+1$, and D_t is one of disagreement indexes D^{EW}, D^{PCA}, and D^{PLS}.

Table 13 presents the results. Generally, the forecasting of the U.S. disagreement indexes continues to exist internationally. There may have to explanations. One is that the international markets comove together (Bekaert, Hodrick, and Zhang, 2009). Another possible reason is that investor disagreements comove together.

5 Conclusion

This paper examines whether disagreements are agreeable, and proposes three aggregate disagreement indexes by aggregating information across 20 proxies. We show that disagreement measures do have a common component that significantly predicts the stock market both in- and out-of-sample. Consistent with the theory developed by Atmaz and Basak (2017), the indexes asymmetrically forecast stock returns, with greater power in high sentiment periods. Moreover, the indexes negatively predict economic activities, and positively predict stock market volatility, illiquidity, and trading volume.

There are some important issues open for future research. First, it will be valuable to apply the aggregate disagreement indexes to other markets, such as bond, commodity, and currency markets, to see whether the predictive power remains. Second, it will be of interest to construct aggregate disagreement indexes at different frequencies, such as daily and weekly, so that investors can use them for real-time investing. Third, as Hong and Stein (2007) posit that there are two main sources of disagreement–differences in information sets and differences in models that investors use to interpret information, it will be interesting to disentangle them.

References

Ajinkya, B. B., Atiase, R. K., Gift, M. J., 1991. Volume of trading and the dispersion in financial analysts' earnings forecasts. The Accounting Review 66, 389–401.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Anderson, E. W., Ghysels, E., Juergens, J. L., 2005. Do heterogeneous beliefs matter for asset pricing? Review of Financial Studies 18, 875–924.

Anderson, E. W., Ghysels, E., Juergens, J. L., 2009. The impact of risk and uncertainty on expected returns. Journal of Financial Economics 94, 233–263.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

Atmaz, A., Basak, S., 2017. Belief dispersion in the stock market. Journal of Finance forthcoming.

Bachmann, R., Elstner, S., Sims, E. R., 2013. Uncertainty and economic activity: evidence from business survey data. American Economic Journal: Macroeconomics 5, 217–49.

Baker, M., Wurgler, J., 2000. The equity share in new issues and aggregate stock returns. Journal of Finance 55, 2219–2257.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61, 1645–1680.

Baker, S. D., Hollifield, B., Osambela, E., 2016. Disagreement, speculation, and aggregate investment. Journal of Financial Economics 119, 210–225.

Baker, S. R., Bloom, N., Davis, S. J., 2016. Measuring economic policy uncertainty. Quarterly Journal of Economics 131, 1593–1636.

Bali, T. G., Brown, S. J., Caglayan, M. O., 2014. Macroeconomic risk and hedge fund returns. Journal of Financial Economics 114, 1–19.

Banerjee, S., 2011. Learning from prices and the dispersion in beliefs. Review of Financial Studies 24, 3025–3068.

Banerjee, S., Kremer, I., 2010. Disagreement and learning: Dynamic patterns of trade. Journal of Finance 65, 1269–1302.

Bekaert, G., Hodrick, R. J., Zhang, X., 2009. International stock return comovements. Journal of Finance 64, 2591–2626.

Berkman, H., Dimitrov, V., Jain, P. C., Koch, P. D., Tice, S., 2009. Sell on the news: differences of opinion, short-sales constraints, and returns around earnings announcements. Journal of Financial Economics 92, 376–399.

Bloom, N., 2009. The impact of uncertainty shocks. Econometrica 77, 623–685.

Boehme, R. D., Danielsen, B. R., Sorescu, S. M., 2006. Short-sale constraints, differences of opinion, and overvaluation. Journal of Financial and Quantitative Analysis 41, 455–487.

Buraschi, A., Whelan, P., 2012. Term structure models with differences in beliefs. Working Paper .

Campbell, J. Y., Grossman, S. J., Wang, J., 1993. Trading volume and serial correlation in stock returns. Quarterly Journal of Economics 108, 905–939.

Campbell, J. Y., Thompson, S. B., 2008. Predicting excess stock returns out of sample: can anything beat the historical average? Review of Financial Studies 21, 1509–1531.

Carlin, B. I., Longstaff, F. A., Matoba, K., 2014. Disagreement and asset prices. Journal of Financial Economics 114, 226–238.

Chen, J., Hong, H., Stein, J. C., 2002. Breadth of ownership and stock returns. Journal of Financial Economics 66, 171–205.

Chen, Y., Eaton, G. W., Paye, B. S., 2016. Micro (structure) before macro? the predictive power of aggregate illiquidity for stock returns and economic activity. Journal of Financial Economics forthcoming.

Choi, H., Mueller, P., Vedolin, A., 2017. Bond variance risk premiums. Review of Finance 21, 987–1022.

Clark, T. E., West, K. D., 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics 138, 291–311.

D'avolio, G., 2002. The market for borrowing stock. Journal of Financial Economics 66, 271–306.

Diether, K. B., Malloy, C. J., Scherbina, A., 2002. Differences of opinion and the cross section of stock returns. Journal of Finance 57, 2113–2141.

Duffie, D., Garleanu, N., Pedersen, L. H., 2002. Securities lending, shorting, and pricing. Journal of Financial Economics 66, 307–339.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Ferreira, M. A., Santa-Clara, P., 2011. Forecasting stock market returns: The sum of the parts is more than the whole. Journal of Financial Economics 100, 514–537.

Garfinkel, J. A., 2009. Measuring investors' opinion divergence. Journal of Accounting Research 47, 1317–1348.

Garfinkel, J. A., Sokobin, J., 2006. Volume, opinion divergence, and returns: a study of post-earnings announcement drift. Journal of Accounting Research 44, 85–112.

Ge, L., Lin, T.-C., Pearson, N. D., 2016. Why does the option to stock volume ratio predict stock returns? Journal of Financial Economics 120, 601–622.

Greenwood, J., Hercowitz, Z., Huffman, G. W., 1988. Investment, capacity utilization, and the real business cycle. American Economic Review 78, 402–417.

Harris, M., Raviv, A., 1993. Differences of opinion make a horse race. Review of Financial Studies 6, 473–506.

Henkel, S. J., Martin, J. S., Nardari, F., 2011. Time-varying short-horizon predictability. Journal of Financial Economics 99, 560–580.

Hong, H., Sraer, D., Yu, J., 2017. Inflation bets on the long bond. Review of Financial Studies 30, 900–947.

Hong, H., Sraer, D. A., 2016. Speculative betas. Journal of Finance 71, 2095–2144.

Hong, H., Stein, J. C., 2003. Differences of opinion, short-sales constraints and market crashes. Review of Financial Studies 16, 487–525.

Hong, H., Stein, J. C., 2007. Disagreement and the stock market. Journal of Economic Perspectives 21, 109–128.

Kelly, B., Pruitt, S., 2013. Market expectations in the cross-section of present values. Journal of Finance 68, 1721–1756.

Kruger, S., 2015. Disagreement and liquidity. Working Paper .

Li, D., Li, G., 2015. Whose beliefs drive trade in the stock market? evidence from household belief dispersion and trading volume. Working Paper .

Li, F. W., 2016. Macro disagreement and the cross-section of stock returns. Review of Asset Pricing Studies 6, 1–45.

Ludvigson, S. C., Ma, S., Ng, S., 2015. Uncertainty and business cycles: exogenous impulse or endogenous response? Working Paper .

Mackowiak, B., Wiederholt, M., 2009. Optimal sticky prices under rational inattention. American Economic Review 99, 769–803.

Miller, E. M., 1977. Risk, uncertainty, and divergence of opinion. Journal of Finance 32, 1151–1168.

Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics 78, 277–309.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Pontiff, J., 2006. Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics 42, 35–52.

Rapach, D. E., Ringgenberg, M. C., Zhou, G., 2016. Short interest and aggregate stock returns. Journal of Financial Economics 121, 46–65.

Rapach, D. E., Strauss, J. K., Zhou, G., 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. Review of Financial Studies 23, 821–862.

Rapach, D. E., Strauss, J. K., Zhou, G., 2013. International stock return predictability: What is the role of the united states? Journal of Finance 68, 1633–1662.

Sadka, R., Scherbina, A., 2007. Analyst disagreement, mispricing, and liquidity. Journal of Finance 62, 2367–2403.

Shalen, C. T., 1993. Volume, volatility, and the dispersion of beliefs. Review of Financial Studies 6, 405–434.

Stambaugh, R. F., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance 70, 1903–1948.

Stock, J. H., Watson, M. W., 2002. Macroeconomic forecasting using diffusion indexes. Journal of Business & Economic Statistics 20, 147–162.

Welch, I., Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455–1508.

Woodford, M., 2003. Interest and prices: foundations of a theory of monetary policy. Princeton University Press.

Yu, J., 2011. Disagreement and return predictability of stock portfolios. Journal of Financial Economics 99, 162–183.

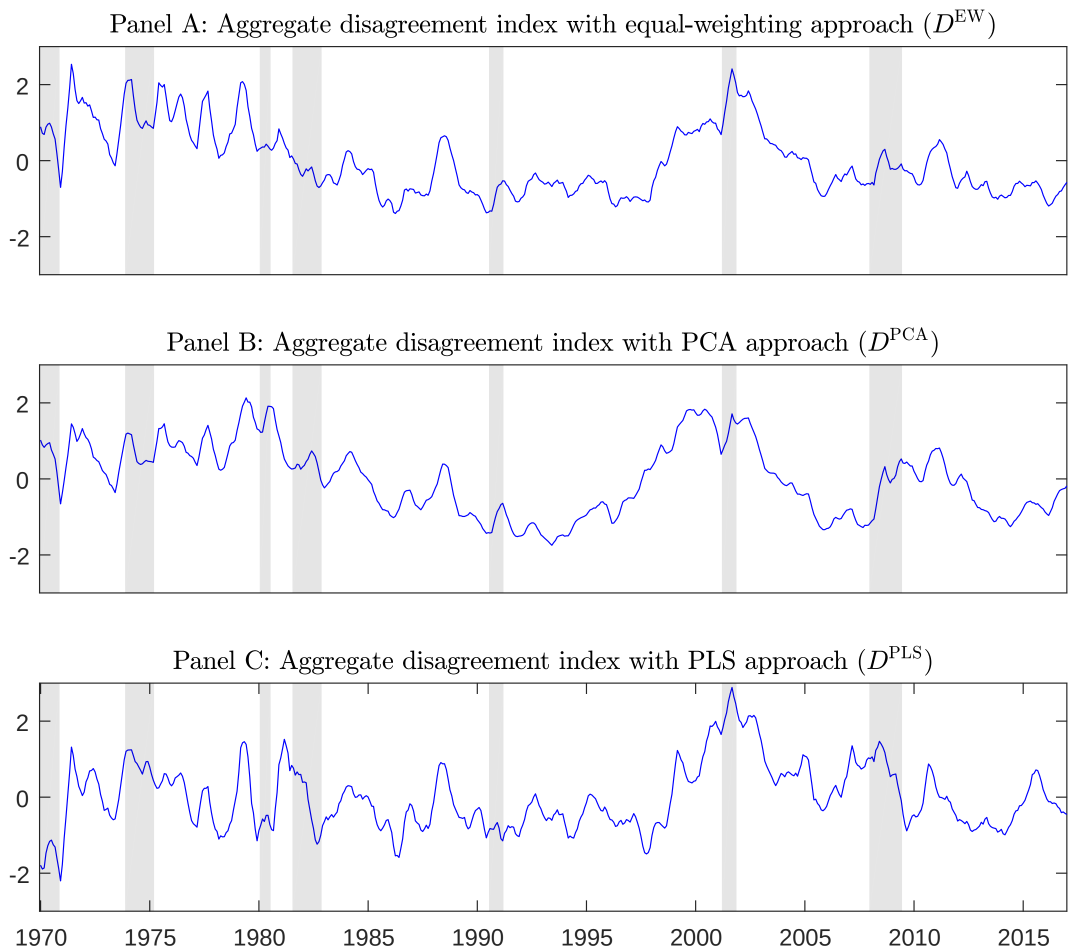

Figure 1 This figure plots the time series of aggregate disagreement indexes constructed by the equal-weighting, PCA, and PLS approaches, respectively. Grey shadow bars denote NBER recessions. The sample period is 1969:12–2016:12.

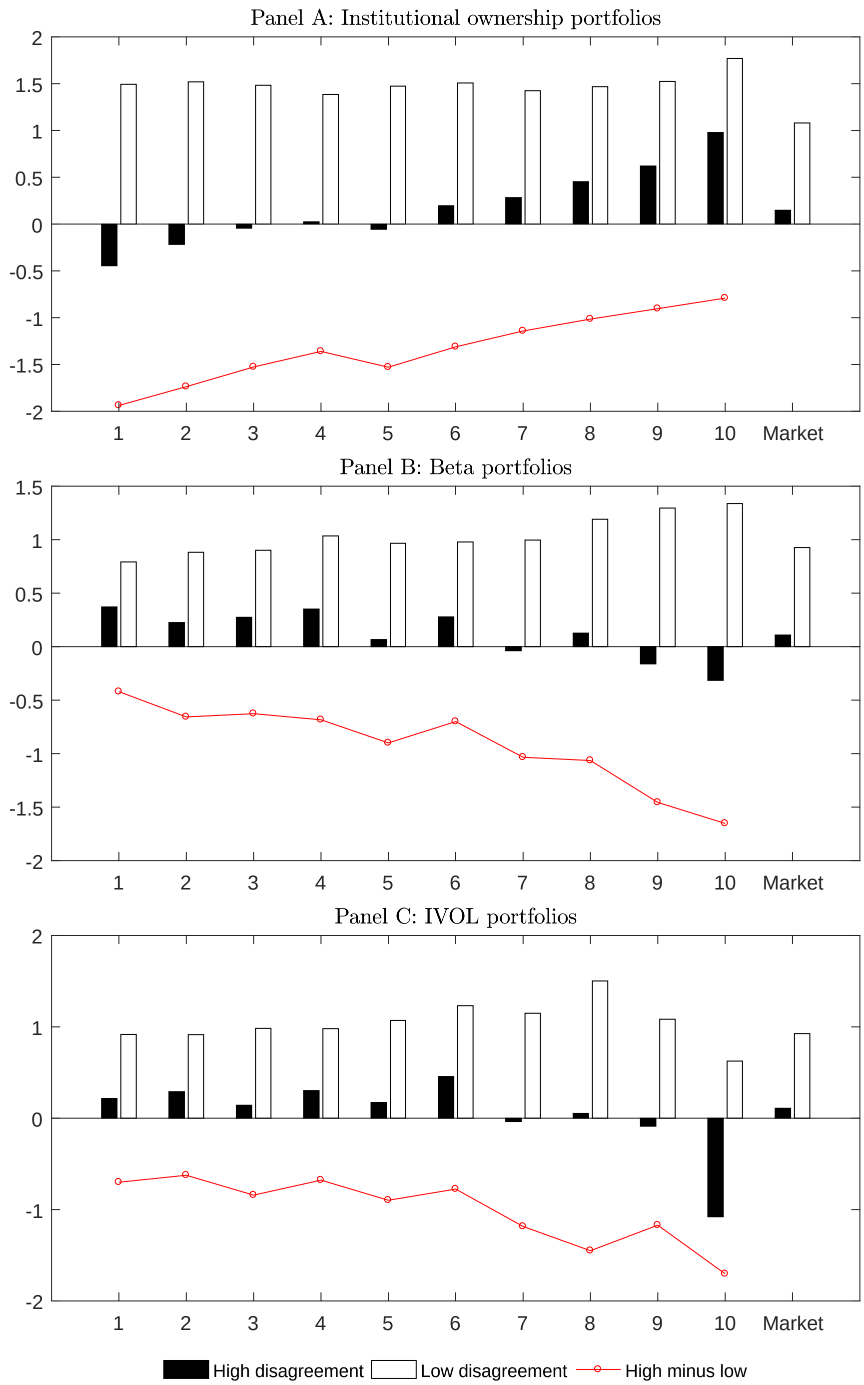

Figure 2 This figure plots the average monthly excess returns of decile portfolios in high and low disagreement periods, where a month is in a high disagreement period if D^{PLS} in the month $t-1$ is above its previous 24-month moving average, and otherwise in a low disagreement period.

Table 1 Summary statistics of individual disagreement measures

The first 9 measures are obtained from the survey of professional forecasters (SPF) at a quarterly frequency, each of which is defined by the level or growth difference between the 75% and 25% percentiles of the forecasts. D^{Yu} and D^{HS} are value- and beta-weighted analyst forecast dispersions in Yu (2011) and Hong and Sraer (2016), respectively. The next six are household belief dispersions on macroeconomic conditions from the Michigan Surveys of Consumers. D^{SUV} is a disagreement measure based on the standardized unexplained trading volume of NYSE (Garfinkel, 2009). D^{IVOL} is the value-weighted idiosyncratic volatility, proposed by Boehme, Danielsen, and Sorescu (2006) as investor disagreement. D^{OID} is a disagreement measure defined by the open interest difference of OEX call and put options.

Panel A: Descriptive statistics

	Sample Period	Obs	Avg	Std	Min	Max	Skew	Kurt
Gross domestic production forecast dispersion (D^{GDP})	1968Q4–2016Q4	196	61.42	40.77	6.80	248.60	1.37	2.88
Gross domestic production growth forecast dispersion (D^{GDPg})	1968Q4–2016Q4	196	1.67	0.70	0.75	4.25	1.06	0.80
Industrial production forecast dispersion (D^{IP})	1968Q4–2016Q4	196	1.98	1.03	0.62	6.10	1.17	1.37
Industrial production growth forecast dispersion (D^{IPg})	1968Q4–2016Q4	196	2.77	1.42	0.84	8.04	1.14	0.98
Unemployment forecast dispersion (D^{UEP})	1968Q4–2016Q4	196	0.32	0.13	0.15	1.04	1.69	4.84
Investment forecast dispersion (D^{INV})	1981Q3–2016Q4	145	22.23	12.58	3.40	57.92	0.52	−0.37
Investment growth forecast dispersion (D^{INVg})	1981Q3–2016Q4	145	3.69	1.17	1.43	8.62	0.75	1.52
Consumer price index forecast dispersion (D^{CPI})	1981Q3–2016Q4	145	0.84	0.31	0.38	2.02	1.32	1.79
3-month T-bill forecast dispersion (D^{TBL})	1981Q3–2016Q4	145	0.47	0.37	0.04	2.96	3.32	16.71
Value-weighted analyst forecast dispersion (D^{Yu})	1981:12–2016:12	421	3.63	0.59	2.64	5.79	1.18	1.01
Beta-weighted analyst forecast dispersion (D^{HS})	1981:12–2016:12	421	4.86	0.89	3.65	7.51	0.77	−0.31
Realized personal financial improvement dispersion (D^{RPF})	1978:01–2016:12	468	−0.44	0.02	−0.50	−0.39	−0.48	−0.25
Expected personal financial improvement dispersion (D^{EPF})	1978:01–2016:12	468	−0.64	0.05	−0.80	−0.50	−0.18	0.17
Business condition dispersion (D^{BC})	1978:01–2016:12	468	−0.42	0.07	−0.69	−0.28	−0.92	0.84
Unemployment condition dispersion (D^{UC})	1978:01–2016:12	468	−0.64	0.08	−0.95	−0.47	−0.56	0.10
Interest rate condition dispersion (D^{IRC})	1978:01–2016:12	468	−0.53	0.08	−0.77	−0.35	−0.26	−0.43
Vehicle purchase condition dispersion (D^{VPC})	1978:01–2016:12	468	−0.50	0.05	−0.68	−0.40	−0.40	0.45
Standardized unexplained volume (D^{SUV})	1968:12–2016:12	565	0.21	1.22	−3.45	3.17	−0.22	−0.54
Idiosyncratic volatility (D^{IVOL})	1968:12–2016:12	565	0.02	0.00	0.01	0.03	1.79	3.65
OEX call/put open interest difference (D^{OID})	1984:02–2016:12	395	0.87	0.09	0.55	1.00	−1.05	0.92

Table 1 (continued)

Panel B: Correlation

	D^{GDP}	D^{GDPg}	D^{IP}	D^{IPg}	D^{UEP}	D^{INV}	D^{INVg}	D^{CPI}	D^{TBL}	D^{Yu}	D^{HS}	D^{RPF}	D^{EPF}	D^{BC}	D^{UC}	D^{IRC}	D^{VPC}	D^{SUV}	D^{IVOL}	D^{OID}
D^{GDP}	1.00																			
D^{GDPg}	0.79	1.00																		
D^{IP}	0.55	0.62	1.00																	
D^{IPg}	0.58	0.74	0.84	1.00																
D^{UEP}	0.49	0.52	0.61	0.56	1.00															
D^{INV}	0.31	0.24	0.31	0.18	0.17	1.00														
D^{INVg}	0.44	0.53	0.56	0.57	0.41	0.65	1.00													
D^{CPI}	0.50	0.57	0.39	0.53	0.35	0.05	0.31	1.00												
D^{TBL}	0.40	0.38	0.37	0.31	0.12	0.08	0.15	0.44	1.00											
D^{Yu}	0.24	0.42	0.41	0.31	0.25	0.29	0.36	0.20	0.08	1.00										
D^{HS}	0.18	0.24	0.53	0.34	0.21	0.24	0.27	0.07	0.09	0.68	1.00									
D^{RPF}	0.02	0.06	−0.05	0.08	−0.10	−0.13	−0.03	0.13	0.27	−0.23	−0.11	1.00								
D^{EPF}	0.07	0.11	0.19	0.15	0.06	0.04	0.12	−0.07	0.09	−0.06	0.09	0.22	1.00							
D^{BC}	−0.31	−0.29	−0.42	−0.28	−0.41	−0.16	−0.20	−0.36	−0.20	−0.27	−0.31	0.19	−0.02	1.00						
D^{UC}	0.23	0.29	0.28	0.39	0.22	−0.08	0.23	0.30	0.16	−0.15	−0.01	0.43	0.42	0.01	1.00					
D^{IRC}	0.38	0.27	0.33	0.32	0.31	0.03	0.00	0.11	0.23	−0.05	0.07	0.09	0.17	−0.14	0.27	1.00				
D^{VPC}	0.08	0.08	−0.05	0.00	0.12	−0.05	0.00	0.23	0.11	0.00	−0.11	0.17	0.02	0.03	0.19	0.02	1.00			
D^{SUV}	−0.01	0.04	−0.19	−0.01	−0.12	−0.02	0.04	0.21	−0.01	−0.12	−0.37	0.15	−0.10	0.23	0.00	−0.12	0.17	1.00		
D^{IVOL}	0.23	0.24	0.30	0.17	0.20	0.56	0.35	−0.18	−0.02	0.46	0.53	−0.27	0.07	−0.22	−0.17	0.07	−0.14	−0.13	1.00	
D^{OID}	0.22	0.11	0.08	0.11	0.13	0.24	0.26	−0.02	−0.06	0.04	−0.06	−0.01	0.05	0.00	0.13	−0.03	0.08	0.16	0.19	1.00

Table 2 Forecasting the market with individual disagreement measures

This table presents the results of predicting the market excess return with individual disagreement measures as:

$$R_{t,t+h} = \alpha + \beta D_t + \varepsilon_{t,t+h},$$

where $R_{t,t+h}$ is the market excess return between months t and $t+h$ ($h = 1, 3$, or 12), and D_t is one of the 20 individual disagreement measures in the first column. The in-sample period is 1969:12–2016:12 and the out-of-sample period is 1991:02–2016:12 because the accurate release date of the Michigan Surveys of Consumers is only available as of January 1991. Reported are regression coefficient, Newey-West t-statistic, in-sample R^2, and out-of-sample R^2_{OS}. Statistical significance for R^2_{OS} is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: $h = 1$				Panel B: $h = 3$				Panel C: $h = 12$			
Disagreement	β	t-stat	R^2	R^2_{OS}	β	t-stat	R^2	R^2_{OS}	β	t-stat	R^2	R^2_{OS}
D^{GDP}	−0.15	−0.73	0.12	−1.69	−0.26*	−1.68	1.00	−5.24	−0.39***	−3.55	8.63	−14.07
D^{GDPg}	−0.29	−1.60	0.43	−3.01	−0.29*	−1.92	1.22	−7.58	−0.27***	−2.78	4.16	−19.55
D^{IP}	−0.11	−0.60	0.06	−2.33	−0.10	−0.67	0.15	−5.35	−0.08	−0.80	0.36	−17.01
D^{IPg}	−0.01	−0.05	0.00	−2.13	−0.20	−1.48	0.57	−9.11	−0.15	−1.41	1.27	−24.11
D^{UEP}	0.13	0.59	0.08	−0.35	0.12	0.72	0.22	−2.14	0.15	1.62	1.25	−7.74
D^{INV}	−0.21	−1.16	0.24	−2.69	−0.26*	−1.66	1.03	−8.54	−0.16	−1.08	1.53	−13.92
D^{INVg}	0.20	1.19	0.22	−0.68	0.04	0.32	0.03	−2.73	0.03	0.19	0.05	−6.63
D^{CPI}	−0.36	−1.62	0.71	−5.44	−0.31**	−2.11	1.45	−27.02	−0.14	−1.10	1.14	−20.03
D^{TBL}	−0.66***	−2.57	2.37	−3.60	−0.55**	−2.55	4.63	−6.31	−0.33**	−2.17	6.67	−7.99
D^{Yu}	−0.32	−1.71	0.66	−3.08	−0.33**	−1.98	2.10	−4.99	−0.33***	−2.64	8.04	−43.22
D^{HS}	−0.14	−0.67	0.14	−2.80	−0.18	−0.89	0.62	−3.02	−0.21	−1.32	3.30	−23.31
D^{RPF}	−0.20	−1.01	0.22	−2.57	−0.06	−0.35	0.06	−4.54	−0.16	−1.57	1.49	−14.70
D^{EPF}	−0.22	−1.01	0.25	−3.05	−0.13	−0.95	0.25	−6.95	−0.04	−0.41	0.07	−15.12
D^{BC}	−0.24	−1.25	0.31	−4.26	−0.12	−0.67	0.21	−7.75	−0.05	−0.36	0.12	−18.85
D^{UC}	−0.05	−0.23	0.01	−2.02	0.02	0.11	0.00	−3.41	−0.03	−0.28	0.05	−15.35
D^{IRC}	−0.23	−0.99	0.28	−1.74	−0.43**	−2.54	2.89	−8.69	−0.44***	−2.98	10.93	−19.28
D^{VPC}	−0.14	−0.69	0.11	−1.89	0.08	0.48	0.09	−2.92	−0.15	−1.33	1.31	−21.00
D^{SUV}	−0.27	−1.61	0.40	−2.44	−0.20	−1.58	0.62	−6.52	−0.20**	−2.03	2.40	−20.93
D^{IVOL}	−0.20	−1.02	0.21	−3.36	−0.19	−1.01	0.52	−9.54	−0.13	−0.98	0.97	−17.53
D^{OID}	−0.20	−0.56	0.08	−2.12	−0.08	−0.26	0.04	−4.80	−0.05	−0.21	0.07	−15.90

Table 3 Forecasting the market with aggregate disagreement index

This table presents the results of predicting the market excess return with aggregate disagreement index as:

$$R_{t,t+h} = \alpha + \beta D_t + \varepsilon_{t,t+h},$$

where $R_{t,t+h}$ is the market excess return between months t and $t+h$ ($h = 1, 3$, or 12), and D_t is one of the aggregate disagreement indexes constructed by the equal-weighting, PCA, and PLS approaches, respectively. Reported are regression coefficient, Newey-West t-statistic, in-sample R^2, and out-of-sample R^2_{OS}. Statistical significance for R^2_{OS} is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Disagreement	β	t-stat	R^2	R^2_{OS}
Panel A: $h = 1$				
D^{EW}	-0.62^{***}	-3.09	1.53	0.13
D^{PCA}	-0.35^{**}	-2.02	0.56	-0.24
D^{PLS}	-0.83^{***}	-3.69	2.59	1.94^{**}
Panel B: $h = 3$				
D^{EW}	-0.61^{***}	-3.30	4.31	1.41^{**}
D^{PCA}	-0.35^{**}	-2.15	1.57	0.00
D^{PLS}	-0.80^{***}	-3.72	6.93	5.29^{***}
Panel C: $h = 12$				
D^{EW}	-0.56^{***}	-3.24	6.97	6.89^{***}
D^{PCA}	-0.24^{*}	-1.77	2.77	-0.38
D^{PLS}	-0.67^{***}	-4.81	18.53	14.32^{***}

Table 4 Weights on individual disagreement measures

This table presents the weights of individual disagreement measures in constructing the aggregate disagreement indexes, which are based on balanced data over 1984:02–2016:12. To make the weights comparable, we normalize the PCA and PLS weights so that the sum of weights equals one.

Disagreement	EW	PCA	PLS
D^{GDP}	5.00	6.21	1.44
D^{GDPg}	5.00	6.21	1.72
D^{IP}	5.00	8.11	2.00
D^{IPg}	5.00	5.99	1.70
D^{UEP}	5.00	5.97	2.73
D^{INV}	5.00	7.30	6.62
D^{INVg}	5.00	7.07	2.37
D^{CPI}	5.00	2.03	8.31
D^{TBL}	5.00	2.85	15.91
D^{Yu}	5.00	9.63	9.46
D^{HS}	5.00	10.12	4.55
D^{RPF}	5.00	4.09	6.63
D^{EPF}	5.00	0.41	4.47
D^{BC}	5.00	6.15	5.99
D^{UC}	5.00	3.24	0.05
D^{IRC}	5.00	1.40	6.04
D^{VPC}	5.00	1.52	6.74
D^{SUV}	5.00	2.96	8.60
D^{IVOL}	5.00	7.94	2.37
D^{OID}	5.00	0.80	2.31

Table 5 Forecasting economic and corporate activities with aggregate disagreement index

The table presents the results of predicting economic and corporate activities with aggregate disagreement index as

$$y_{t+1} = \alpha + \beta D_t + \sum_{i=1}^{12} \lambda_i y_{t-i+1} + \varepsilon_{t+1},$$

for monthly data, and

$$y_{q+1} = \alpha + \beta D_q + \sum_{i=1}^{4} \lambda_i y_{q-i+1} + \varepsilon_{q+1},$$

for quarterly data. The economic and corporate activities include Chicago fed national activity index (CFNAI), industrial production growth, real personal consumption expenditure (consumption), unemployment, private gross domestic investment (investment), aggregate equity issuance (Baker and Wurgler, 2000), business inventory, and capacity utilization (Greenwood, Hercowitz, and Huffman, 1988). Reported are regression coefficient, Newey-West t-statistic, and R^2. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: D^{EW}			Panel B: D^{PCA}			Panel C: D^{PLS}		
y	β	t-stat	R^2	β	t-stat	R^2	β	t-stat	R^2
CFNAI	−0.13	−0.32	27.12	0.11	0.31	27.11	-0.97^{**}	−2.38	27.77
Industrial production	−0.15	−0.43	21.59	−0.01	−0.02	21.57	-1.21^{***}	−3.15	22.86
Consumption	−0.01	−0.43	61.21	0.00	0.19	61.19	-0.06^{**}	−2.26	61.54
Unemployment	0.11	1.20	16.63	0.07	0.98	17.94	0.32^{***}	3.47	17.94
Investment (quarterly)	−0.32	−0.33	7.70	0.21	0.22	7.67	-3.28^{***}	−2.91	12.06
Equity issuance	−0.09	−0.39	33.68	−0.03	−0.14	33.66	-0.47^{***}	−2.02	34.11
Business inventory	-0.59^{*}	−1.91	59.71	−0.37	−1.54	59.49	-0.59^{**}	−2.44	59.94
Capacity utilization	−0.25	−0.89	19.77	−0.20	−0.88	19.75	-0.71^{**}	−2.30	20.43

Table 6 Forecasting asymmetry of aggregate disagreement index

Panel A reports the in- and out-of-sample R^2s of forecasting the market excess return with aggregate disagreement index in high and low sentiment periods, where a month is defined as high (low) if the last year's sentiment index of Baker and Wurgler (2006) is positive (negative). Panel B presents the results of forecasting the market excess return with a state-dependent regression, where the state is determined by sentiment. Statistical significance for R^2_{OS} is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Performance of $R_{t+1} = \alpha + \beta D_t + \varepsilon_{t+1}$ in high and low sentiment periods

	In-sample R^2		Out-of-sample R^2_{OS}	
Disagreement	High	Low	High	Low
D^{EW}	2.89	−0.02	−0.23	0.49
D^{PCA}	1.47	−0.49	−0.52	0.07
D^{PLS}	4.74	0.08	3.53**	−0.22

Panel B: $R_{t+1} = \alpha + \beta_1 I_t^{\mathrm{high}} D_t + \beta_2 I_t^{\mathrm{low}} D_t + \varepsilon_{t+1}$

Disagreement	β_1	t-stat	β_2	t-stat	R^2
D^{EW}	−1.00***	−3.57	−0.30	−1.09	2.01
D^{PCA}	−0.72**	−2.66	−0.04	−0.19	1.07
D^{PLS}	−1.02***	−3.63	−0.36	−0.94	2.92

Table 7 Asset allocation results

This table reports the portfolio performance of a mean-variance investor with risk-aversion $\gamma = 3$ or 5 for predicting the market excess return with aggregate disagreement index. The investor allocates his wealth monthly among the market and the risk-free asset by applying the out-of-sample forecasts based on the disagreement indexes D^{EW}, D^{PCA}, and D^{PLS}, respectively. CER gain is the annualized certainty equivalent return difference between applying the disagreement forecast and applying the historical average forecast. Monthly Sharpe ratio is mean portfolio return in excess of the risk-free rate divided by its standard deviation. The portfolio weight is estimated recursively, using data available at the forecast formation month t. The investment period is 1991:02–2016:12. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

	No transaction cost		50 bps transaction costs	
	CER gain (%)	Sharpe ratio	CER gain (%)	Sharpe ratio
Panel B: Risk aversion $\gamma = 3$				
D^{EW}	0.50	0.10	−0.01	0.08
D^{PCA}	−0.34	0.08	−0.50	0.08
D^{PLS}	4.39***	0.18***	3.58**	0.16**
Panel C: Risk aversion $\gamma = 5$				
D^{EW}	−0.85	0.07	−1.27	0.05
D^{PCA}	−0.55	0.07	−0.67	0.06
D^{PLS}	3.48***	0.18***	2.84**	0.16**

Table 8 Predicting market volatility

This table presents the results of predicting market volatility with aggregate disagreement as:

$$y_{t+1} = \alpha + \beta_1 D_t + \beta_2 y_t + \varepsilon_{t+1},$$

where y_{t+1} is VIX (Panel A) or market realized volatility (Panel B), and D_t is one of the three aggregate disagreement indexes constructed by the equal-wighting, PCA, and PLS approaches, respectively. Reported are regression coefficient, Newey-West t-statistic, and R^2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Disagreement	β_1	t-stat	β_2	t-stat	R^2
Panel A: VIX					
D^{EW}	0.74***	2.89	0.81***	21.44	71.17
D^{PCA}	0.87***	3.51	0.78***	15.99	71.59
D^{PLS}	0.57**	2.44	0.82***	24.90	71.12
Panel B: Market realized volatility					
D^{EW}	0.02	1.18	0.67***	14.39	44.90
D^{PCA}	0.03***	2.84	0.65***	12.93	45.56
D^{PLS}	0.04***	2.82	0.65***	14.46	45.49

Table 9 Predicting market liquidity

This table presents the results of predicting market aggregate liquidity with aggregate disagreement as:

$$y_{t+1} = \alpha + \beta_1 D_t + \beta_2 y_t + \varepsilon_{t+1},$$

where y_{t+1} is Amihud (2002) illiquidity or Pástor and Stambaugh (2003) liquidity in month $t+1$, and D_t is one of the three aggregate disagreement indexes constructed by the equal-wighting, PCA, and PLS approaches, respectively. Reported are regression coefficient, Newey-West t-statistic, and R^2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Disagreement	β_1	t-stat	β_2	t-stat	R^2
Panel A: Amihud illiquidity					
D^{EW}	0.20^{**}	2.43	0.80^{***}	14.37	66.52
D^{PCA}	0.24^{***}	2.84	0.79^{***}	13.11	66.71
D^{PLS}	0.20^{**}	2.54	0.80^{***}	16.29	66.52
Panel B: Pástor-Stambaugh liquidity					
D^{EW}	-0.02^{***}	-4.01	0.07	1.29	5.87
D^{PCA}	-0.01^{***}	-3.65	0.09	1.45	4.74
D^{PLS}	-0.01^{**}	-1.97	0.10	1.50	3.35

Table 10 Forecasting market trading volume

The table presents the results of predicting the market turnover (proxy of trading volume) with aggregate disagreement as:

$$\text{Volume}_{t+1} = \alpha + \beta_1 D_t + \beta_2 \text{Volume}_t + \varepsilon_{t+1},$$

where D_t is one of the three aggregate disagreement indexes constructed by the equal-weighting, PCA, and PLS approaches, respectively. Volume_t is the turnover on NYSE, S&P 500 ETF (SPY), or NASDAQ ETF (QQQ). Following Campbell, Grossman, and Wang (1993) and Baker and Wurgler (2006), we define turnover as the current trading volume minus its previous 60-month moving average to remove possible trends. Reported are regression coefficients, Newey-West t-statistic, and R^2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	β_1	t-stat	β_2	t-stat	R^2
Panel A: D^{EW}					
NYSE	0.18	0.60	0.84***	25.33	70.41
SPY	2.47*	1.79	0.80***	18.25	65.11
QQQ	4.43***	3.52	0.68***	7.77	73.02
Panel B: D^{PCA}					
NYSE	0.16	0.50	0.84***	24.91	70.41
SPY	−0.47	−0.39	0.81***	18.04	64.88
QQQ	1.28**	2.20	0.80***	16.42	70.95
Panel C: D^{PLS}					
NYSE	0.84**	2.00	0.83***	23.03	70.55
SPY	4.87***	2.76	0.76***	15.37	66.11
QQQ	3.04***	3.03	0.72***	9.92	72.21

Table 11 Comparison with economic variables

Panel A presents the results of predicting market excess return as:

$$R_{t+1} = \alpha + \psi Z_t + \varepsilon_{t+1},$$

where Z_t is one of the 14 economic predictors in Welch and Goyal (2008). Panels B, C, and D report the results of forecasting market excess return with aggregate disagreement and economic variable as:

$$R_{t+1} = \alpha + \beta D_t + \psi Z_t + \varepsilon_{t+1},$$

where D_t is one of the three aggregate disagreement indexes constructed by the equal-weighting, PCA, and PLS approaches, respectively. Reported are regression coefficient and R^2. The sample period is 1969:12–2016:12. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Univariate		Panel B: D^{EW}			Panel C: D^{PCA}			Panel D: D^{PLS}		
Economic predictor	ψ	R^2	β	ψ	R^2	β	ψ	R^2	β	ψ	R^2
Dividend-price ratio	0.15	0.12	−0.63***	0.19	1.72	−0.37**	0.18	0.73	−0.86***	−0.08	2.61
Dividend yield	0.17	0.15	−0.63***	0.21	1.76	−0.37**	0.20	0.77	−0.85***	−0.07	2.61
Earning-price ratio	0.09	0.04	−0.63***	0.14	1.63	−0.37**	0.13	0.65	−0.84***	−0.06	2.60
Dividend payout ratio	0.07	0.02	−0.61***	0.05	1.54	−0.35**	0.05	0.57	−0.83***	−0.01	2.59
Stock sample variance	−0.19	0.19	−0.60***	−0.13	1.62	−0.32*	−0.12	0.62	−0.82***	−0.01	2.59
Book-to-market ratio	−0.01	0.00	−0.68***	0.19	1.70	−0.40**	0.13	0.63	−0.84***	−0.10	2.64
Net equity expansion	−0.07	0.03	−0.67***	0.13	1.61	−0.35*	0.01	0.56	−0.84***	−0.12	2.66
Treasury bill rate	−0.26	0.36	−0.59***	−0.19	1.72	−0.30	−0.19	0.73	−0.85***	−0.31	3.08
Long-term bond yield	−0.15	0.12	−0.61***	−0.11	1.59	−0.33*	−0.09	0.60	−0.86***	−0.23	2.86
Long-term bond return	0.42**	0.90	−0.59***	0.39**	2.31	−0.33*	0.40**	1.40	−0.81***	0.40**	3.41
Term spread	−0.41**	0.87	−0.58***	−0.36**	2.20	−0.29	−0.37**	1.23	−0.86***	−0.45**	3.63
Default yield spread	−0.17	0.15	−0.63***	−0.20	1.74	−0.41**	−0.25	0.87	−0.84***	−0.22	2.82
Default return spread	0.35	0.64	−0.62***	0.36	2.19	−0.36**	0.36	1.24	−0.81***	0.32	3.11
Inflation rate	0.01	0.00	−0.67***	0.16	1.66	−0.38**	0.10	0.61	−0.83***	0.03	2.59

Table 12 Comparison with uncertainty measures

Panel A presents the correlations between disagreement and eight uncertainty measures, including economic uncertainty index (UNC) in Bali, Brown, and Caglayan (2014), treasury implied volatility (TIV) in Choi, Mueller, and Vedolin (2017), economic policy uncertainty (EPU) in Baker, Bloom, and Davis (2016), financial uncertainty (FU), macro uncertainty (MU), and real economy uncertainty (RU) in Ludvigson, Ma, and Ng (2015), sample variance (SVAR) in Welch and Goyal (2008), and CBOE implied volatility index (VIX). Panel B presents the results of forecasting market excess return with uncertainty as:

$$R_{t+1} = \alpha + \psi U_t + \varepsilon_{t+1},$$

where U_t is one of eight uncertainty measures. Panels C, D, and E present the results of forecasting the market excess return with aggregate disagreement and uncertainty as:

$$R_{t+1} = \alpha + \beta D_t + \psi U_t + \varepsilon_{t+1},$$

where D_t is one of the three disagreement indexes constructed by the equal-weighting, PCA, and PLS approaches, respectively. Reported are regression coefficient and R^2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Correlation between aggregate disagreement and uncertainty measures	UNC	TIV	EPU	FU	MU	RU	SVAR	VIX
D^{EW}	0.29	0.31	0.15	0.40	0.26	0.37	0.12	0.35
D^{PCA}	0.38	0.21	0.15	0.54	0.36	0.40	0.26	0.52
D^{PLS}	0.19	0.34	0.10	0.26	0.24	0.04	0.25	0.28

	Panel B: Univariate		Panel C: D^{EW}			Panel D: D^{PCA}			Panel E: D^{PLS}		
Uncertainty	ψ	R^2	β	ψ	R^2	β	ψ	R^2	β	ψ	R^2
UNC	−0.13	0.09	-0.92^{***}	0.08	2.61	−0.38	0.01	0.64	-1.06^{***}	0.06	5.24
TIV	−0.37	0.71	-0.66^{*}	−0.21	1.97	−0.17	−0.33	0.85	-0.89^{***}	−0.08	4.02
EPU	0.19	0.18	-0.76^{***}	0.27	1.82	−0.36	0.24	0.72	-0.89^{***}	0.27	3.40
FU	-0.60^{**}	1.83	-0.41^{*}	−0.45	2.41	−0.01	−0.59	1.84	-0.69^{***}	−0.44	3.53
MU	−0.45	1.04	-0.52^{**}	−0.33	2.05	−0.20	−0.38	1.20	-0.74^{***}	−0.30	3.01
RU	−0.27	0.36	-0.58^{**}	−0.07	1.55	−0.28	−0.16	0.66	-0.82^{***}	−0.24	2.87
SVAR	−0.19	0.19	-0.60^{***}	−0.13	1.61	-0.32^{*}	−0.12	0.62	-0.82^{***}	−0.01	2.58
VIX	0.03	0.00	-0.90^{***}	0.27	2.39	−0.42	0.23	0.70	-1.05^{***}	0.29	4.86

Table 13 Forecasting international markets

The table presents the results of predicting ten international stock markets with the U.S. aggregate disagreement index as:

$$R^j_{t+1} = \alpha + \beta D_t + \varepsilon_{t+1},$$

where R^j_{t+1} is country j's market excess return and D_t is one of the three aggregate disagreement indexes constructed by the equal-weighting, PCA, and PLS approaches, respectively. Reported are regression coefficient, Newey-West t-statistic, and R^2. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: D^{EW}			Panel B: D^{PCA}			Panel C: D^{PLS}		
Country	β	t-stat	R^2	β	t-stat	R^2	β	t-stat	R^2
Belgium	-0.80^{***}	-3.40	1.88	-0.53^{**}	-2.51	0.93	-1.00^{***}	-3.34	2.79
Canada	-0.25	-1.05	0.21	-0.03	-0.12	0.00	-0.61^{**}	-2.40	1.23
France	-0.55^{*}	-1.71	0.71	-0.19	-0.69	0.10	-0.75^{**}	-2.33	1.26
Germany	-0.71^{**}	-2.40	1.23	-0.49^{*}	-1.83	0.67	-0.72^{**}	-2.22	1.21
Italy	-0.75^{**}	-2.26	0.96	-0.22	-0.60	0.09	-0.91^{***}	-2.70	1.36
Japan	-0.15	-0.45	0.06	-0.15	-0.52	0.07	-0.50^{*}	-1.66	0.64
Netherlands	-0.69^{***}	-2.63	1.40	-0.38^{*}	-1.75	0.50	-0.85^{***}	-3.04	2.05
Sweden	-0.77^{**}	-2.30	1.15	-0.47	-1.28	0.48	-0.91^{**}	-2.39	1.52
Switzerland	-0.64^{***}	-2.62	1.46	-0.50^{**}	-2.42	1.00	-0.72^{***}	-2.94	1.76
UK	-0.34	-1.03	0.29	-0.16	-0.75	0.07	-0.60^{**}	-2.17	0.85