Internet Appendix

Are Disagreements Agreeable? Evidence from Information Aggregation

Appendix A. Six LASSO Methods

In this section, for each method we explain how to construct the out-of-sample forecast in month t for the return in month $t+1$.

Equal-weight LASSO In month t, we choose J out of K individual disagreement measures via the following LASSO optimization problem:

$$\max_{\beta} \sum_{j=1}^{t-1} \left(R_{t+1} - \sum_{k=1}^{K} \beta_k D_t^k\right)^2 + \lambda \sum_{k=1}^{K} |\beta_k|, \tag{A1}$$

where D_t^k is the observation of individual disagreement measure k ($k = 1, \cdots, K$) in month t. Then we construct an equal-weight disagreement index as

$$D_t^{\text{EW}} = \sum_{j=1}^{J} \tilde{D}_t^j, \tag{A2}$$

where $\tilde{D}_t^1$ through $\tilde{D}_t^J$ are the selected individual disagreement measures in month t. Based on the predictive regression (7), we estimate the expected market return as

$$\hat{R}_{t+1}^{\text{EW-LASSO}} = \hat{\alpha}_t + \hat{\beta}_t D_t^{\text{EW}}. \tag{A3}$$

Empirically, Chinco, Clark-Joseph, and Ye (2019) find that the LASSO performs well in identifying sparse and high-frequency return predictors in a cross-sectional framework.

Combination LASSO To reduce model instability and uncertainty, Han, He, Rapach, and Zhou (2019) propose a combination LASSO method to improve the forecasting power of individual stock return predictors, which directly combines individual stock return forecasts. In this paper, suppose $\hat{R}^k_{t+1}$ is the market return forecast based on disagreement measure D^k_t and M is the initial sample size for parameter training. In month t, the combination LASSO estimates the expected market return as

$$\hat{R}^{\text{C-LASSO}}_{t+1} = \sum_{k=1}^{K} \hat{\beta}_k \hat{R}^k_{t+1}, \tag{A4}$$

where $\hat{\beta} = (\hat{\beta}_1, \cdots, \hat{\beta}_K)$ is the estimate via the following LASSO optimization problem,

$$\max_{\beta} \quad \sum_{j=M+1}^{t} \left(R_{t+1} - \sum_{k=1}^{K} \beta_k \hat{R}^k_{t+1}\right)^2 + \lambda \sum_{k=1}^{K} |\beta_k|. \tag{A5}$$

Encompassing LASSO Suppose $\hat{R}_{t+1}$ is the market return forecast based on all the individual disagreement measures via a multivariate predictive regression. Han, He, Rapach, and Zhou (2019) propose an encompassing LASSO method as

$$\hat{R}^{\text{E-LASSO}}_{t+1} = \theta_t \hat{R}_{t+1} + (1-\theta_t)\hat{R}^{\text{C-LASSO}}_{t+1}, \tag{A6}$$

where θ_t is estimated with the Harvey, Leybourne, and Newbold (1998) forecast encompassing test.

Adaptive LASSO As in Freyberger, Neuhierl, and Weber (2020), the adaptive LASSO weights the terms in the penalty of (A5) to encourage small first-round coefficient estimates to be set to zero,

$$\max_{\beta} \quad \sum_{j=M+1}^{t} \left(R_{t+1} - \sum_{k=1}^{K} \beta_k \hat{R}^k_{t+1}\right)^2 + \lambda \sum_{k=1}^{K} w_k |\beta_k|. \tag{A7}$$

and estimate the expected market return as

$$\hat{R}^{\text{A-LASSO}}_{t+1} = \sum_{k=1}^{K} \hat{\beta}_k \hat{R}^k_{t+1}, \tag{A8}$$

where $w_i = 1/|\hat{\beta}_k|^{\nu}$, $\hat{\beta}_k$ is the univariate predictive regression estimate, and $\nu > 0$.

Egalitarian LASSO Instead of shrinking the coefficient to zero, Diebold and Shin (2019) propose to shrink it to the simple average,

$$\max_{\beta} \sum_{j=M+1}^{t} \Big(R_{t+1} - \sum_{k=1}^{K} \beta_k \hat{R}_{t+1}^{k}\Big)^2 + \lambda \sum_{k=1}^{K} \Big|\beta_k - \frac{1}{K}\Big|. \tag{A9}$$

Then the expected market return can be estimated as

$$\hat{R}_{t+1}^{\text{Eg-LASSO}} = \sum_{k=1}^{K} \hat{\beta}_k \hat{R}_{t+1}^{k}. \tag{A10}$$

Elastic net To handle the potential highly correlated return forecasts, one may solve for the following optimization problem,

$$\max_{\beta} \sum_{j=1}^{t} \Big(R_t - \sum_{i=1}^{N} \beta_i \hat{R}_{i,t}\Big)^2 + \lambda_1 \sum_{i=1}^{N} |\beta_i| + \lambda_2 \sum_{i=1}^{N} \beta_i^2, \tag{A11}$$

and estimate the expected market return as

$$\hat{R}_{t+1}^{\text{EN-LASSO}} = \sum_{k=1}^{K} \hat{\beta}_k \hat{R}_{t+1}^{k}. \tag{A12}$$

Empirically, Kozak, Nagel, and Santosh (2020) show that the elastic net is powerful in predicting stock returns in a cross-sectional framework.

In all the six LASSO-related methods, the tuning parameter λ is chosen via the corrected version of the Akaike information criterion (AICc). Han, He, Rapach, and Zhou (2019) show that the AICc performs quantitatively similar as alternative cross validation criteria.

Appendix B. Forecasting economic activities

This section shows that the disagreement index negatively predicts future economic activities. Specifically, we consider six macro variables as the proxy of economic activities, including the CFNAI, industrial production growth, unemployment rate, aggregate equity issuance, total business inventory, and capacity utilization.

The macro variables are adjusted for seasonality and annualized for ease of exposition. To control for the autocorrelations, we follow Allen, Bali, and Tang (2012) and run the following regression:

$$y_{t+1} = \alpha + \beta D_t + \sum_{i=1}^{12} \lambda_i y_{t-i+1} + \varepsilon_{t+1}, \tag{A1}$$

where y_{t+1} is one of the macro variables.

Table A4 shows that the disagreement index negatively predicts future economic activities. For instance, a one-standard deviation increase in the disagreement index predicts a 0.93% decrease in the CFNAI and a 0.22% increase in unemployment, respectively.

Appendix C. Individual disagreement measures

In this section, we report the data sources and definitions of individual disagreement measures.

Disagreement measures based on professional forecasts (level): Gross domestic production forecast dispersion (D^{GDP}), industrial production forecast dispersion (D^{IP}), consumption forecast dispersion (D^{CON}), investment forecast dispersion (D^{INV}), housing starts forecast dispersion (D^{HSG}), unemployment rate forecast dispersion (D^{UEP}), consumer price index forecast dispersion (D^{CPI}) and 3-month T-bill rate forecast dispersion (D^{TBL}).

- Source: Survey of Professional Forecasts (SPF).
- Frequency: Quarterly.
- Definition: At each survey date t, the quarterly forecast horizons are t, t+1, t+2, t+3, and t+4. Each quarter horizon's dispersion is 75% percentile F^{75th} forecast in excess of 25% percentile forecast F^{25th},

$$D_{t+k} = F_{t+k}^{75th} - F_{t+k}^{25th}, \quad k = 0, 1, 2, 3, 4.$$

For each variable, the quarter t's D^{Macro} is defined as the average of five horizons' dispersion:

$$D_t^{\text{MACRO}} = (D_t + D_{t+1} + D_{t+2} + D_{t+3} + D_{t+4})/5,$$

where MACRO = GDP, IP, CON, INV, HSG, UEP, CPI and TBL.

- Periods: D^{GDP}, D^{IP}, D^{CON}, D^{HSG}, D^{UEP}: 1968:Q4–2018:Q4;
  D^{INV}, D^{CPI}, D^{TBL}: 1981:Q3–2018:Q4.

Disagreement measures based on professional forecasts (growth): Gross domestic production growth forecast dispersion (D^{GDPg}), industrial production growth forecast dispersion (D^{IPg}), consumption growth forecast dispersion (D^{CONg}), investment growth forecast dispersion (D^{INVg}) and housing starts growth dispersion (D^{HSGg}).

- Source: Survey of Professional Forecasts (SPF).
- Frequency: Quarterly.
- Definition: At each survey date t, the forecast quarterly horizons are t, t+1, t+2, t+3, and t+4. We define the implied quarter over quarter (Q/Q) forecast growth $\hat{g}$ (in annualized percentage points) as

$$\hat{g}_{t+k} = 100 \cdot \left[\left(\frac{F_{t+k}}{F_{t+k-1}} \right)^4 - 1 \right] \quad k = 0,\ 1,\ 2,\ 3,\ 4.$$

  Next, each horizon's growth rate dispersion is difference between 75% percentile implied growth rate $\hat{g}^{75th}$ and 25% percentile implied growth rate $\hat{g}^{25th}$,

$$D_{t+k}^{\text{g}} = g_{t+k}^{75th} - g_{t+k}^{25th}, \quad k = 0,\ 1,\ 2,\ 3,\ 4.$$

  For each variable, the quarter t's D^{MACROg} is defined as the average of five horizons' growth dispersion:

$$D_t^{\text{MACROg}} = (D_t^g + D_{t+1}^g + D_{t+2}^g + D_{t+3}^g + D_{t+4}^g)/5,$$

  where MACRO = GDP, IP, CON, INV and HSG.

- Periods: D^{GDPg}, D^{IPg}, D^{CONg}, D^{HSGg}: 1968:Q4–2018:Q4;

  D^{INVg}: 1981:Q3–2018:Q4.

Disagreement measures based on analyst forecasts : Value-weighted analyst forecast dispersion (D^{Yu}) and beta-weighted analyst forecast dispersion (D^{HS}).

- Source: IBES, CRSP and Kenneth French's Data Library.
- Frequency: Monthly.
- Definition: For each firm i in month t, we obtain LTG EPS forecast standard deviations D_t^i from IBES unadjusted summary database. We also obtain monthly stock closing price and share outstanding from CRSP to compute the market cap. We only include the common stocks (CRSP item SHRCD = 10 or 11) listed on NYSE/AMEX/NASDAQ. The valued-weighted analyst forecast dispersion is defined as

$$D_t^{\text{Yu}} = \frac{\sum_i \text{MKTCAP}_{i,t} \cdot D_{i,t}}{\sum_i \text{MKTCAP}_{i,t}}.$$

  To estimate the stock betas, we obtain daily stock return from CRSP, U.S. Treasury bill rate and market premium from Kenneth French's data library. Equity premiums are in excess of U.S. Treasury bill rate. Following Hong and Sraer (2016), we drop the microcap stocks in lowest two NYSE size deciles. At each month end for each firm, the beta is estimated by regressing daily equity premium on current and up to 5 lags of market premium using last 12 month returns,

$$R_d^i = \alpha^i + \beta_0^i \text{MKT}_d + \beta_1^i \text{MKT}_{d-1} + \beta_2^i \text{MKT}_{d-2} + \beta_{d-3}^i \text{MKT}_t + \beta_{d-4}^i \text{MKT}_t + \beta_{d-5}^i \text{MKT}_t + \varepsilon_t.$$

  At each month end, we define the beta weights as the absolute sum of the six beta estimates,

$$\beta^i = |\beta_0^i + \beta_1^i + \beta_2^i + \beta_3^i + \beta_4^i + \beta_5^i|.$$

After achieving the beta weights, the beta-weighted analyst forecast dispersion is defined as

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

- Periods: 1981:12–2018:12.

Disagreement measures based on household forecasts: Realized personal financial improvement dispersion (D^{RPF}), expected personal financial improvement dispersion (D^{EPF}), business condition dispersion (D^{BC}), unemployment condition dispersion (D^{UC}), interest rate condition dispersion (D^{IRC}), house purchase condition dispersion (D^{HOM}).

- Source: Michigan University Survey of Consumers Attitudes (SCA).

- Frequency: Monthly.

- Definition: Six measures are constructed from six survey questions, respectively. These questions are about 1) D^{RPF}: consumer's realized opinions on current personal financial condition compared with one year ago; 2) D^{EPF}: consumer's expectation on personal financial condition in the following year; 3) D^{BC} consumer's expectation on business condition in the following year; 4) D^{UC} consumer's expectation on unemployment condition in the following year; 5) D^{IRC}: consumer's expectation on interest rate condition in the following year; 6) D^{HOM}: consumer's expectation on house purchase condition in the following year. The surveyed consumers reply in three categories, better (good), same (depends), and bad (worse). We label the proportion of these three categories as P_{positive}, P_{neutral}, and P_{negative}. We capture surveyed consumers' reply dispersion by unevenly weighted negative Herfindahl index as:

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

  where $w_{\mathrm{positive}} = 1$, $w_{\mathrm{neutral}} = 2$, $w_{\mathrm{negative}} = 1$.

- Periods: 1978:01–2018:12.

Disagreement based on unexplained stock trading volume: Standardized unexplained volume (D^{SUV}).

- Source: Pinnacle.
- Frequency: Monthly.
- Definition: We obtain the monthly aggregate trading volume, 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 on a rolling basis as

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

where R^+ is the positive market returns, and R^- is the negative market returns. We take the last value of ε in each rolling regression and standardize it with the variance of ε as that month's standardized unexplained trading volume,

$$D_t^{SUV} = \frac{\varepsilon_t}{S_t}.$$

- Periods: 1968:12–2018:12.

Disagreement based on idiosyncratic volatility: Idiosyncratic volatility (D^{IVOL}).

- Source: CRSP and Kenneth French's Data Library.
- Frequency: Monthly.
- Definition: We use the common stock (CRSP item SHRCD = 10 or 11) listed on NYSE/AMEX/NASDAQ daily stock returns in excess of U.S. treasury bill rate as excess return. Next, at each month end for each firm, we run rolling regression of excess return on contemporaneous Fama-French three factors with a 12-month rolling window,

$$R_t^i = \alpha^i + \beta_1^i \text{MKT}_t + \beta_2^i \text{SMB}_t + \beta_3^i \text{HML}_t + \varepsilon_t.$$

We estimate the firm level idiosyncratic volatility as the standard deviation of the residual term. Next, we use value-weighted method to summarize the firm level idiosyncratic volatility to achieve the market aggregate level idiosyncratic volatility.

- Periods: 1968:12–2018:12.

Disagreement based on option open interest: OEX call/put open interest difference (D^{OID}).

- Source: Pinnacle.
- Frequency: Monthly.
- Definition: In each month end, we use the absolute difference between OEX call and put option interest scaled by their sum to capture how evenly distributed between call and put options. Next, we use the one minus the scaled difference as the option market disagreement measure:
$$D_t^{\mathrm{OID}} = 1 - \frac{|\mathrm{COI}_t - \mathrm{POI}_t|}{|\mathrm{COI}_t + \mathrm{POI}_t|},$$
- Periods: 1984:02–2018:12.

We follow the procedures described in Section 3 to construct the PLS disagreement index. Since the data panel is unbalance, for in-sample analyses, we normalize the PLS disagreement index within three separate periods: 1) December 1969 to December 1978 when only the disagreement measures based on professional forecasts from SPF are available, 2) January 1979 to January 1985 when the measures based on analyst forecasts and household forecasts start to join, and 3) February 1985 onwards when all individual measures become available. When normalizing within the whole sample period, the slope for predicting the next one month market return is $\beta = -0.72$ (t-value $= -2.78$) with an in-sample R^2 of 2.71%. For out-of-sample analysis, we do not standardize the PLS disagreement index and all the inputs to the forecast are constructed using data that are observed no later than month t.

Fig. A1. This figure plots the individual disagreement measures selected by the LASSO-related techniques at each point in time when conducting out-of-sample forecasting over 1991:02–2018:12.

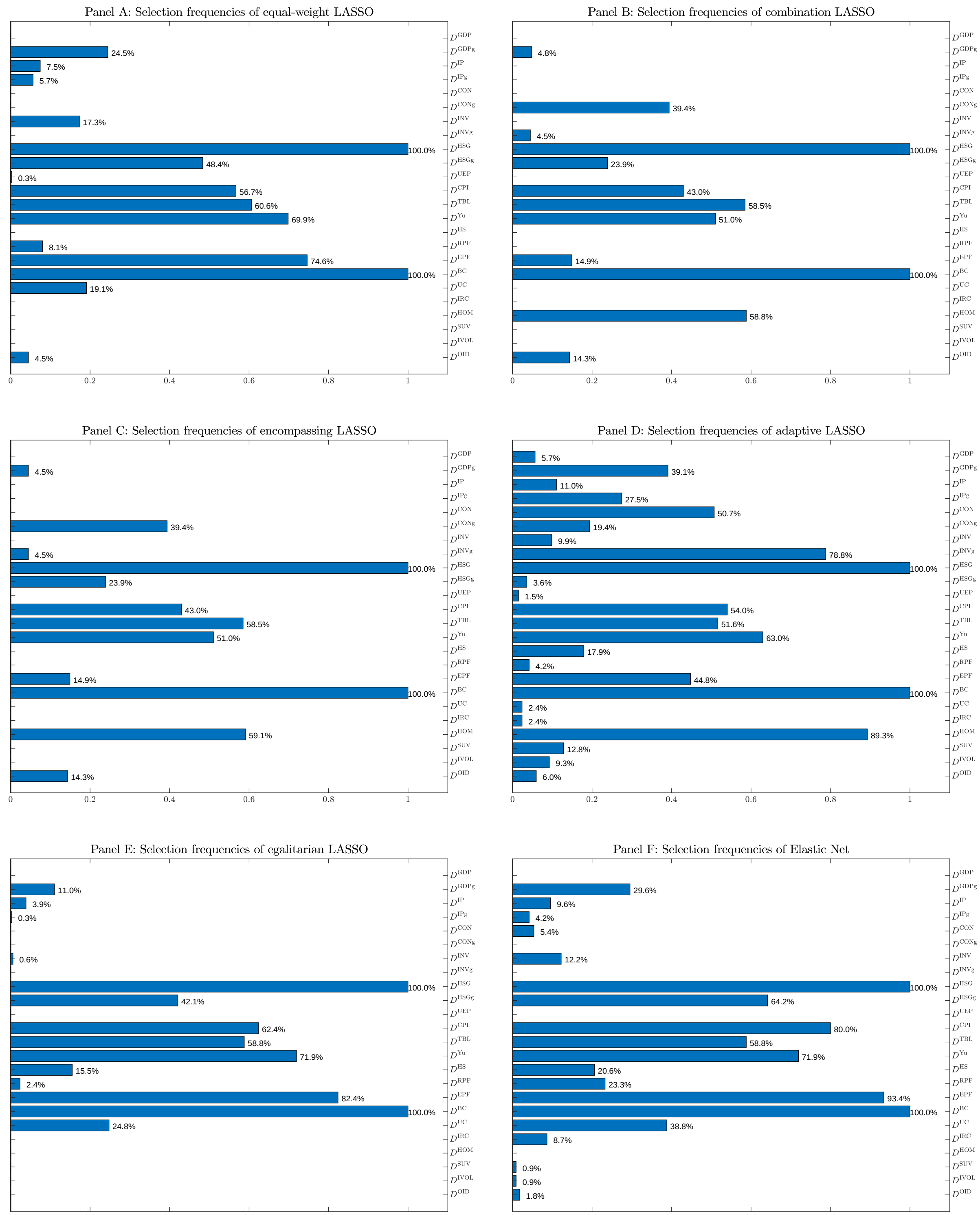

Fig. A2. This figure plots the selection frequency of each individual disagreement measure over the 1991:02–2018:12 out-of-sample period.

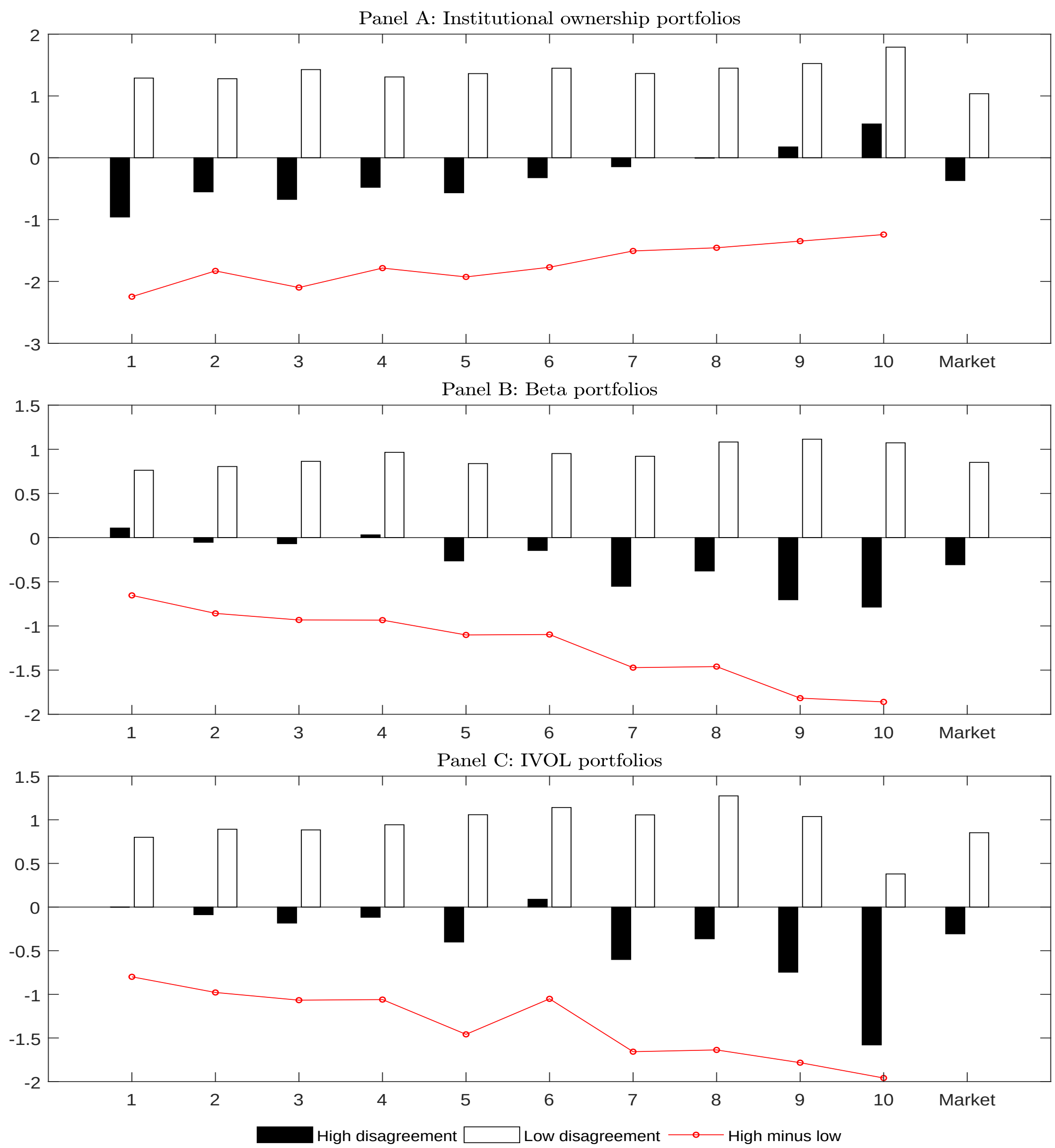

Fig. A3. This figure plots the average monthly excess returns of decile portfolios in high and low disagreement periods, where a month is in a high disagreement period if D^{PLS} in month $t-1$ is above its previous 24-month moving average, and otherwise in a low disagreement period.

Table A1 Correlations between individual disagreement measures

This table reports the pairwise correlations of 24 individual disagreement measures used in this paper. The first 13 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 75th and 25th percentiles of the forecasts. D^{Yu} and D^{HS} are value- and beta-weighted analyst forecast dispersions (Yu, 2011; Hong and Sraer, 2016). The next six are household belief dispersions on macroeconomic conditions from the Michigan survey of consumers attitudes. D^{SUV} is a disagreement measure based on the standardized unexplained trading volume of NYSE stocks (Garfinkel, 2009). D^{IVOL} is the value-weighted idiosyncratic volatility proposed by Boehme, Danielsen, and Sorescu (2006) as a measure of investor disagreement. D^{OID} is a disagreement measure defined by the open interest difference of OEX call and put options (Ge, Lin, and Pearson, 2016).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1 D^{GDP}	1.00																							
2 D^{GDPg}	0.80	1.00																						
3 D^{IP}	0.54	0.56	1.00																					
4 D^{IPg}	0.56	0.67	0.83	1.00																				
5 D^{CON}	0.62	0.61	0.49	0.51	1.00																			
6 D^{CONg}	0.66	0.71	0.54	0.60	0.82	1.00																		
7 D^{INV}	0.45	0.42	0.38	0.34	0.49	0.42	1.00																	
8 D^{INVg}	0.42	0.52	0.50	0.58	0.32	0.49	0.68	1.00																
9 D^{HSG}	0.38	0.35	0.22	0.31	0.24	0.26	−0.06	0.04	1.00															
10 D^{HSGg}	0.50	0.54	0.32	0.40	0.28	0.37	0.16	0.35	0.51	1.00														
11 D^{UEP}	0.47	0.50	0.61	0.54	0.42	0.54	0.26	0.41	0.19	0.43	1.00													
12 D^{CPI}	0.43	0.39	0.32	0.45	0.26	0.36	0.14	0.26	0.43	0.44	0.31	1.00												
13 D^{TBL}	0.38	0.35	0.37	0.29	0.13	0.19	0.10	0.12	0.29	0.15	0.16	0.35	1.00											
14 D^{Yu}	0.26	0.39	0.35	0.26	0.26	0.33	0.32	0.33	0.16	0.21	0.22	0.15	0.08	1.00										
15 D^{HS}	0.23	0.25	0.42	0.30	0.20	0.18	0.21	0.27	0.08	0.01	0.16	0.07	0.06	0.64	1.00									
16 D^{RPF}	0.01	0.00	−0.03	0.07	−0.09	−0.05	−0.07	0.00	0.08	0.04	−0.14	0.05	0.16	−0.30	−0.13	1.00								
17 D^{EPF}	0.10	0.13	0.20	0.16	−0.01	0.07	−0.01	0.13	0.05	0.03	0.07	−0.03	0.19	−0.02	0.12	0.16	1.00							
18 D^{BC}	−0.22	−0.23	−0.28	−0.19	−0.22	−0.24	−0.08	−0.11	−0.28	−0.19	−0.41	−0.36	−0.14	−0.31	−0.25	0.23	−0.02	1.00						
19 D^{UC}	0.14	0.18	0.24	0.32	−0.10	0.09	−0.08	0.22	0.05	0.23	0.15	0.21	0.17	−0.13	0.06	0.27	0.45	0.01	1.00					
20 D^{IRC}	0.36	0.28	0.34	0.33	0.24	0.25	0.09	0.08	0.30	0.34	0.28	0.17	0.31	0.04	0.14	0.07	0.20	−0.14	0.26	1.00				
21 D^{HOM}	0.06	0.03	−0.04	−0.03	−0.05	0.07	−0.11	−0.10	0.13	−0.05	−0.04	0.25	0.34	0.17	0.09	−0.07	−0.03	−0.14	−0.07	−0.01	1.00			
22 D^{SUV}	0.00	0.00	−0.17	0.00	0.10	0.10	0.03	0.05	0.18	0.09	−0.11	0.14	−0.10	−0.19	−0.19	0.19	−0.12	0.19	−0.10	−0.09	0.06	1.00		
23 D^{IVOL}	0.32	0.34	0.36	0.29	0.37	0.31	0.50	0.41	0.20	0.19	0.27	0.00	−0.03	0.53	0.69	−0.23	0.03	−0.24	−0.11	0.15	−0.07	−0.09	1.00	
24 D^{OID}	0.22	0.19	0.13	0.17	0.15	0.17	0.24	0.31	0.11	0.21	0.17	0.00	−0.01	0.12	0.16	−0.05	0.13	−0.04	0.21	0.00	0.07	0.08	0.20	1.00

Table A2 Forecasting market returns with different moment PLS disagreement indexes

This table presents the regression slopes, Newey-West t-values, in-sample R^2s, and out-of-sample R^2_{OS}s of predicting market returns with the first to sixth moment PLS disagreement indexes, respectively. 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 $H_A : R^2_{OS} > 0$. The in- and out-of-sample periods are 1969:12–2018:12 and 1991:02–2018:12, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Moment	β	t-value	R^2	R^2_{OS}
1st	-0.83^{***}	-3.96	2.52	1.56^{**}
2nd	-0.49	-1.06	0.21	-0.87
3rd	-0.20	-0.56	0.05	-0.29
4th	-0.01	-0.02	0.00	-0.24
5th	-0.10	-0.56	0.06	-0.16
6th	-0.12	-1.27	0.29	-0.08

Table A3 Disagreement with market volatility and trading volume: Robustness check

Panel A presents the results of predicting the volume-volatility correlation with the disagreement index:

$$\text{Correlation}_{t+1} = \alpha + \beta D_t + \varepsilon_{t+1},$$

where the correlation in month $t+1$ refers to the correlation between the daily change in turnover of NYSE stocks and the daily change in volatility within month $t+1$. Realized volatility, realized semi-volatility, and median realized volatility are estimated based on the S&P 500 index returns from 5-minute intervals (Andersen, Dobrev, and Schaumburg, 2012), and futures realized volatility is estimated based on the S&P 500 index futures contract returns from 5-minute intervals (Johnson, 2019). Panel B presents the results of the following regression:

$$\text{Volatility}_{t+1} = \alpha + \beta_1 \text{D\_Volume}_t + \beta_2 \text{Volume}_t^{\circ} + \varepsilon_{t+1}.$$

D_Volume is the disagreement-related volume and extracted with the PLS method, and Volume$^{\circ}$ is the residual of regressing volume on D_Volume. D_Volatility is the disagreement-related volatility. Following Hamilton (2018), we apply AR(4) to both trading volume and market volatility to remove potential trends and expected information. Reported are regression coefficient, Newey-West t-value, and R^2. The sample period is 2000:01–2018:12 for the first three volatility measures and 1990:01–2015:12 for the last one. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Predicting volatility-volume correlation			
	β	t-value	R^2
Realized volatility	5.22***	3.36	4.02
Realized semi-volatility	3.25	1.51	1.27
Median realized volatility	3.21**	2.05	1.57
Futures realized volatility	5.30***	3.97	4.68

Panel B: Predicting market volatility						
	β_1	t-value	β_2	t-value	R^2	Corr(D_Volume, D_Volatility)
Realized volatility	3.17*	1.80	0.74	0.60	1.45	0.45
Realized semi-volatility	3.29*	1.79	0.71	0.50	1.32	0.44
Median realized volatility	4.19**	2.33	1.15	0.77	2.20	0.59
Futures realized volatility	5.84***	4.90	1.22	1.13	5.43	0.62

Table A4 Forecasting economic activities with disagreement

The table presents the regression slope, Newey-West t-value, and R^2 of predicting economic activities with the disagreement index as

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

Economic activities include Chicago Fed National Activity Index (CFNAI), industrial production growth, unemployment, aggregate equity issuance (Baker and Wurgler, 2000), business inventory, and capacity utilization. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Economic activity	β	t-value	R^2
CFNAI	-0.93^{**}	-2.05	27.13
Industrial production	-1.04^{***}	-2.68	20.92
Unemployment	0.22^{**}	2.22	18.06
Equity issuance	-4.73^{**}	-2.46	29.35
Business inventory	-0.57^{***}	-3.49	58.52
Capacity utilization	-0.72^{***}	-2.30	20.00

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