When the Options Market Disagrees

Mathieu Fournier
HEC Montreal

Ruslan Goyenko
McGill University

Gunnar Grass
HEC Montreal

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Abstract

Using equity options order flows we construct cross-sectional and aggregate disagreement measures by investor type: customer (client accounts) and intermediary (proprietary trading desks). The sources of disagreement differ between investor types, which has important pricing implications. Client-account originated order flows disagree about both positive and negative news while negatively predicting stock returns. When aggregated, client disagreement positively predicts future market volatility (VIX), and common sentiment indexes. This is consistent with the optimistic investor theory. While also negatively predicting stock returns, prop-desk accounts disagree about negative news on the cross-sectional stock level, and negative macro-economic news on the aggregate market level. Prop-desk disagreement negatively predicts S&P500 returns, common sentiment indexes, and client disagreement. This is consistent with the rational expectations theory provided that the source of disagreement is macro-economic uncertainty. Overall, aggregate market-wide client disagreement reflects market sentiment and prop-desk disagreement can be considered as an index of uncertainty.

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Contact author: Ruslan Goyenko, McGill University, 1001 Sherbrooke st West, QC Canada, H3A 1G5; Email: ruslan.goyenko@mcgill.ca

1. Introduction.

While theoretical literature on how heterogeneity of beliefs affects asset prices is growing, the empirical evidence is rather scarce largely due to data limitations. Theoretically, dispersion of opinion can decrease or increase expected stock returns. If differences in opinion reflect limited market participation, they will lead to optimistic investors bidding prices up, asset overvaluation and subsequent reversal resulting in lower future returns (Miller (1977)). Alternatively, if the source of disagreement is uncertainty about asset valuations driven by volatility and poor information, then current prices can be depressed and expected returns will be higher (Wang (1993)).

To the date there is no clear agreement in the empirical literature on how disagreement affects asset valuations. Diether, Malloy, and Scherbina (2002), and Goetzmann and Massa (2005) document a negative relationship between disagreement and future stock returns. They attribute it to the fact that investors who have lowest valuations do not trade (Miller (1977)). In contrast, Banerjee (2011) theoretically argues that when investors condition on prices to infer private information of others, as in rational equilibrium models, the relationship between disagreement and expected returns is positive. However, the reverse is true when the dispersion of opinions is driven by heterogeneous priors. Empirically, he finds support for rational equilibrium models, and shows that on aggregate the positive relationship between disagreement and expected stock returns dominates.

Testing theoretical predictions without well-defined proxy for disagreement is challenging. For instance, Banerjee (2011) constructs various proxies of disagreement from analyst forecast dispersion. He finds that the results are sensitive to the proxy used. The limitations of analyst forecast to test the pricing implications of disagreement has been discussed in several studies (see, among others, Goetzmann and Massa (2005), Johnson (2004)), and it is commonly acknowledged that measures directly capturing dispersion of investors' trades are needed.

In this paper we fill this gap in the literature and construct a measure of disagreement based on actual investors' trades in equity options market using signed trading volumes. The data are obtained from the Chicago Board Options Exchange (CBOE) and the International Securities Exchange (ISE), and capture more than 60% of overall signed trading options volume in the US.

The data also identify a client-initiated (customer) and a firm (proprietary trading desk of an institution) initiated orders. Our measure of trade dispersion (hereafter Disagreement) is the highest when the signed trading options volume exhibit similar number of contracts establishing positive and negative exposure to the prices of underlying. This measure has a clear advantage over commonly used analyst forecast dispersion measures as a proxy for disagreement. It is unbiased, and rather than forecast it is actual investors' trades based.

We construct a measure of trade dispersion (disagreement) by an investor type, customer vs. firm. Goyenko (2015) shows that these two investor types trade for different reasons: their net order flows are highly negatively correlated, and firm orders are on average providing liquidity to customers. Given the opposite trading strategies between these two investor types, we hypothesize that they can disagree for different reasons.

This is indeed what we find. First, both customer and firm disagreements negatively predict future stock returns, which is consistent with Miller (1977). However, this predictability is driven by different information about firm fundamentals. We combine our firm specific disagreement measures with a novel news database from media press releases about firm fundamentals. We find that customer disagreement negatively predicts stock returns after conditioning on both, positive and negative news releases about underlying stocks. Thus customer order flows disagree similarly about both positive and negative information releases about fundamentals. In contrast, negative predictability by prop-desks disagreement comes entirely from negative news releases about underlying assets. They seem to largely disagree about how bad the bad news are, which is not consistent with Miller (1977) but can be consistent with rational expectation theories.

Second, the negative predictability of stock returns by customer and prop-desk disagreements is quite strong and lasts for several weeks. It is robust to inclusion lagged stock returns, stock illiquidity, market capitalization, volatility, stock and options order imbalances. The economic profits of zero investment long-short strategies, i.e. buying low and selling high disagreement portfolio and unwinding the position one or two weeks after, result in between 4 to 6% annualized Fama-French-Carhart risk adjusted abnormal returns. Moreover, double-sorting on both firm and customer disagreement uncovers the highest High minus Low strategy profits of 12% in abnormal risk adjusted annual returns which are observed for firm disagreement sorted portfolios in the middle-quintile of customer disagreement sorted portfolios. Thus, the prop-desk seem to disagree on the cross-section of stocks where customer order flows are relatively neutral.

This further highlights the importance of treating these two investor types separately, since not only they pay attention to different information about fundamentals, but also to a different cross-section of stocks.

Third, to better understand the difference between the two types of disagreements we analyze their market wide implications. Given that customer order flows disagree about both positive and negative news, we can expect it to lead to higher market-wide volatility since divergence in trades is observed regardless of the direction of information. In contrast, prop-desk order flows have a clear directional disagreement about negative news. Given strong cross-sectional evidence, we expect that higher firm disagreement leads to lower market returns overall. To understand better the fundamentals of the news that these disagreements are capturing, we construct two types of aggregate market wide News indexes: (i) value-weighted index of firm specifics news (News-Firm) that we use previously in the cross-sectional regressions, and (ii) the US macro news (News-Macro) index which includes news about economic output, consumption, employment, foreign exchange, interest rates, credit, the balance of payments, production, and housing, amongst others. We use vector auto regression analysis (VAR) with five variables, firm and customer disagreements, return on S&P500 index, changes in VIX as a proxy for the market-wide volatility, and two versions of the News index.

We do confirm our hypotheses that higher customer disagreement positively and highly significantly predicts changes in VIX, and higher firm disagreement robustly negatively predicts S&P500 return in the same VAR dynamics. This highlights not only cross-sectional but also market wide importance of these disagreements for asset pricing.

Our analysis reveals distinct sources of disagreement across the two type of investors using two news indexes. While News-Firm has no predictability for customer and firm disagreements, News-Macro negatively and significantly predict prop-desk level market wide disagreement, i.e. more positive macro-news decrease firm-level disagreement, and more negative macro-news increase firm disagreement. This highlights an important difference between firm and customer disagreements. Professional investors (financial intermediaries like prop-desks) disagree largely about bad aggregate macro-news. Their disagreement about macro-economic fundamentals has negative impact on financial markets. Overall, firm and customer disagreements have negative and significant lead-lag relationship which is consistent with the different fundamental nature they disagree on.

Finally, given the results above, we suggest that customer market wide disagreement can be an actual investors-trades based proxy for market wide sentiment, while firm disagreement is an index of macro-economic uncertainty. Anderson et al (2009) argue that uncertainty and risk are not only capturing different fundamentals but also affect asset prices differently. As such, we hypothesize that two disagreement measures should have different impact on known sentiment indexes: customer disagreement should positively predict sentiment indexes, and firm disagreement should have negative predictability. We use two common in the literature sentiment indexes: Baker and Wurgler (2006) and the University of Michigan consumer sentiment indexes. In the tri-variate VAR dynamics where we use both customer and firm disagreements and one of the indexes, we find that customer disagreement positively predicts both sentiment indexes and the reverse is not true. Firm disagreement significantly negatively predicts University of Michigan sentiment index which is expected given that lower macro-economic outlook would decrease consumer sentiment.

The rest of the paper is organized as follows. In Section II we discuss our findings in the context of the existing literature. Section III describes the data and main variable construction. Section IV reports cross-sectional analysis. Section V provides time series (VAR) analysis, and Section VI concludes.

II. Discussion of Results

We contribute to the existing literature in three important ways. First, we construct a novel measure of disagreement based on actual investors' trades. Second, we suggests two investors' types with different disagreements and different market wide asset pricing applications of their disagreements. Third, we are able to identify two distinct information sets these investors disagree about.

Our customer disagreement results co-exist and support over-optimistic investor Miller (1977) theory. The customer order flows are overoptimistic not only about positive news about firm fundamentals but also negative news, i.e. both optimists and pessimists diverge in their opinions, and thus do not require short sales constraints for Miller's theory to hold. This in turn supports the literature which argues that Miller (1977) theory can hold even in the absence of short-sale constraints (see for example, Hong and Stein (2007), Banerjee (2011)). Moreover, given that

customer disagreement is positively and significantly associated with future sentiment indexes further supports its overall optimistic nature.

There is also a growing literature which favors rational expectation explanation of differences in opinion and their effect on stock returns (Wang (1993), Banerjee (2011), Banerjee and Green (2015)). According to this literature, investors learn about fraction of informed traders in the market and thus about the level of asymmetric information by observing market prices. It argues that when there are more less informed investors, the level of asymmetric information is higher, current prices contain less information, and thus expected risk premia is higher.

For example, Banerjee and Green (2015) nested both rational expectation and difference in opinion in their theoretical model where investors are uncertain about the fraction of informed investors in the market. They conclude that when uninformed traders assign a low probability to other traders being informed, higher disagreement leads to higher returns, and volatility, and the opposite is true. This literature however never specifies the origin of information asymmetry: micro or firm specific, i.e. information about future cash flows, versus macro-economic or market-wide, i.e. information about future discount rates. For example, an increase in short-term interest rates (expansionary monetary policy) results in decrease in stock prices (Rigobon and Sack, 2004). If investors disagree about future increase in interest rates, their divergence of opinion will results in negative return predictability, as it has been often the case with recent FED announcements about interest rate policies.

In the context of rational expectation theory, financial intermediaries such as prop-desks can be considered as more informed investors, while customer accounts can be treated as relatively less informed. We however find that their opinions, measured by the actual trades they make, diverge about different fundamentals. Customer order flows diverge about asset fundamentals while the opinion of more informed traders diverge about macro-economic uncertainty and pessimistic macro-outlooks. Here, the fraction of informed investors is less informed about negative macro-economic trends resulting in higher information asymmetry about how bad macro-outlook is. Hence, we suggest that the information asymmetry theory can be largely applied to prop-desk disagreement. We, however, uncover the new source of information asymmetry for the rational expectation theory. Rather than information about future cash flows on a firm level, the agents in this theory could be disputing whether negative macro-economic news are short- or long-lived, and thus the future interest rates changes. Those who think that the persistence of negative

macro-trend is short-lived would expect an increase in future short-term interest rates, and lower, rather than higher future expected returns. Thus, even under rational expectation theory but conditioning on a monetary policy uncertainty, we still can expect negative predictability from dispersion of opinions to future stock returns. This resonates Anderson, Ghysels, and Juergens (2005) who develop a general equilibrium model with disagreement being a risk factor. They find that short-term disagreement negatively predicts stock returns and long-term disagreement has positive effect on expected stock returns. Given our trading data frequency we can only capture short-term (weekly or daily) disagreement, and thus support Anderson et al. (2005) argument.

Alternatively, the dispersion of opinion among professional investors such as prop-desks can be treated as a proxy for the market-wide uncertainty. Anderson, Ghysels, and Juergens (2009) construct a proxy for market uncertainty using the degree of disagreement of professional forecasters. They find that uncertainty is different from risk, and has different impact on returns than risks. Similar to Anderson et al. (2009), we also find that past uncertainty has no predictive relations for future risk (measured by VIX). Unlike Anderson et al (2009) we find that our measure of uncertainty negatively predicts market returns in the weekly data, while the authors report positive predictability in their quarterly sample. Perhaps the results can be reconciled with short-term versus long-term disagreement applications for stock returns as in Anderson et al. (2005), with our measure of prop-desk uncertainty measuring short-term uncertainty.

Finally, our measure of disagreement based on options trading data has several advantages compared to all previously used measures in the literature which are largely based on forecasts dispersions. For example, if one uses stock trades only (Goetzmann and Massa (2005)) [1], pessimistic investors might not be trading because of their negative priors and short sale constraints, or because they are mistakenly assumed to be pessimistic since it is not possible to "measure" their opinion. Theoretically, disagreement effect on stock prices can arise even without short sales constraints (Banerjee (2011)) making identification of pessimistic investors even harder. In the options market, on the contrary, all priors are revealed via directional trades, i.e. synthetic short versus synthetic long positions, which our disagreement measure captures. We thus

[1] Goetzmann and Massa (2005) use Odean (1998, 1999) data of a sample of small investors for 1991-1995, and construct their dispersion (heterogeneity) measure based on investors' characteristics such as age, occupation, and income levels.

consider our disagreement measures more advantageous compared to others previously used by researchers.

III. Data and Descriptive Statistics.

The main data this paper uses are from the Chicago Board Options Exchange (CBOE) and the International Securities Exchange (ISE) Open/Close Volume. Both exchanges provide daily trading volumes for individual equity options with buy or sell identifiers. The volumes are further categorized into open buy, close buy, and open sell, close sell for call and put contracts. Open buy call (OBC) or put (OBP) for example implies initiating long call (put) position, i.e. positive (negative) exposure to the price of underlying, and close buy (CBC) call (put (CBP)) means covering previously open sell/written positons. Open sell call (OSC) indicates opening short/written position, and close sell (CSC) is covering previously open long position (OBC), and similarly for puts.

Since ISE initiated its data coverage in 2005, we obtain CBOE data starting from 2005, and overall the sample covers 2005 – 2013 period. We merge CBOE and ISE data with OptionMetrics to obtain options greeks (ex. options delta, Δ). The resulting dataset is further merged with CRSP daily stock files to obtain stock returns, prices, volume and shares outstanding information. Overall the paper uses all common stocks (CRSP share codes 10 or 11) listed on NYSE/AMEX/NASDAQ and which also have options traded on CBOE or ISE

We define disagreement for each options series for calls and puts respectively as follows:

$$DISC = \frac{(OBC\Delta + CBC\Delta + OSC\Delta + CSC\Delta) - |(OBC\Delta + CBC\Delta) - (OSC\Delta + CSC\Delta)|}{OBC + CBC + OSC + CSC}$$

$$DISP = \frac{(OBP\Delta + CBP\Delta + OSP\Delta + CSP\Delta) - |(OBP\Delta + CBP\Delta) - (OSP\Delta + CSP\Delta)|}{OBP + CBP + OSP + CSP}$$

To control for options moneyness, all volumes in the numerator are multiplied by their options series delta. We eliminate series with 10 days left to expiration to avoid capturing rollover trades. We also eliminate extreme deltas exceeding 0.98 or lower than 0.02 for calls, and lower than -0.98 or higher than -0.02 for puts. To compute disagreement we separately use call and put

contracts, and then we add them together. This approach has a few advantages. First, call contracts is a more active market compared to put contracts measured in total transacting volumes and number of trades per day (see Christoffersen et al (2015)). Second, written covered call position is the most common trade among retail investors (Lakonishok et al. (2007)). Third, customer accounts initiate trades in call contracts significantly more than in put contracts, while prop-desks use both, calls and puts (Goyenko (2015)).

Given these empirically observed stylized differences between calls and puts, we find it important to first compute disagreement for calls and puts separately. Our overall disagreement measure (*DIS*) is the sum of *DISC* and *DISP*. [2] We use open buy and close buy as buy volume overall, and similarly for sell volume. Buy volume indicates positive exposure to stock price for calls, and sell volume means negative exposure, and opposite holds for puts. If total buy and sell volumes are similar, *DIS* will reach the highest level. Since the numerator is scaled by options deltas, it will always be below 1 for calls (*DISC*) or puts (*DISP*), and below 2 for overall *DIS*.

We further compute *DIS* for two types of investors, customer (client accounts) and firm (financial intermediaries such as prop-desks), *DISCustom* and *DISFirm* respectively. The data allow clearly identifying only these two categories, with firm orders are exclusively attributed to proprietary trading desks of institutions. Our motivation to consider customer vs. firm accounts separately is primarily driven by the evidence reported in Goyenko (2015), who finds that they have negatively correlated net order flows, and prop-desks are on average providing liquidity to customer order flows. He also finds that when it comes to informed trading around corporate events, prop-desk are normally trade in the right direction of anticipated news announcements while customer order flows are overly optimistic and always tend to take positive exposure to the prices of underlying regardless of whether future announcements are positive or negative firm cash flow surprises. Overall, these two investor types not only trade against each other, but also trade on different information priors about firm fundamentals.

Since we analyze the dispersion of opinion about stocks measured with options trades it is important to control for whether our measure is not dominated/captured by price pressures in the stock market, i.e. stock order imbalances, *ImbalStock*, or stocks illiquidity, *ILS*. Stock order

[2] The only concern with this approach is that we might be capturing disagreement about volatility rather than underlying stock values. We separately constructed disagreement measure using straddles only (a direct trade on volatility) and we find no results for straddle-based disagreement measures.

imbalances are computed as total dollar buy volume minus dollar sell volume and then divided by the sum of both, dollar buy and sell volumes for each day, and using intraday Trade and Quotes (TAQ) data. The intraday volume, buy or sell, is signed using Lee and Ready (1991) algorithm. The measure of stock illiquidity, is also computed using TAQ data and defined as dollar volume weighted relative effective spread for each day for each firm in the sample.

To control for firm characteristics we also use market capitalization, *Size*, and volatility ($\sigma(Ret_i)$) measured as squared return.

One of the concerns about our disagreement measure is that it might be capturing options order imbalances. By construction however the disagreement measure is orthogonal to order imbalances, since when *DIS* reaches the highest value, the order imbalances are close to zero. To avoid however for possible overlap in information we want to capture, we also control for options order imbalances.

Options order imbalances are computed similar to Bollen and Whaley (2004):

$$IMB_k = \frac{\sum_{i=1}^{N}(\Delta Buy_i - \Delta Sell_i)}{\sum_{i=1}^{N}(Buy_i + Sell_i)}$$

where buy volume is $Buy_i = Open\ Buy_i + Close\ Buy_i$, and sell volume is $Sell_i = Open\ Sell_i + Close\ Sell_i$ for options series i. For each firm k, *IMB* is averaged across all available options series for each day for all contracts, and then separately for call and put contracts, and by customer and firm order categories (*IMB Call Custom/Firm, IMB Put Custom/Firm*). Similarly, *DIS, DISCustom* and *DISFirm* are first computed on a series level and then are averaged on a firm level.

To avoid possible market microstructure biases associated with using daily data, the analysis below uses weekly data, where *DIS*, *DISCustom* and *DISFirm, IMB Call Custom/Firm, IMB Put Custom/Firm, StockIMB* and *ILS* are averaged across daily data for a week.[3]

One can also suspect that our disagreement measures may somewhat be closely associated with common proxies for private information. To address this concern, we construct and use as control variables Pan and Poteshman (2006) put-call volume ratios, and Johnson and So (2012)

[3] We repeat our analysis using daily data and the results are only stronger both in economic and statistical magnitudes.

options to stock volume ratios. Similar to Pan and Poteshman (2006) we define put-call volume ratio as:

$$PP_{i,t} = \frac{OBP_{i,t}}{OBP_{i,t} + OBC_{i,t}}$$

where $OBP_{i,t}$ and $OBC_{i,t}$ are open buy of put and call contracts respectively for a given stock. Moreover, since Pan and Poteshman (2006) find that predictability for stock returns mostly comes from customer initiated *PP* measure, we use only customer orders while constructing this variable. Similarly to Johnson and So (2012) we define *OS* as the ratio of log option volume to stock volume. Here again all estimates are first computed daily on a firm level and then averaged per week.

Table 1 presents summary statistics of all variables. In the rest of the text we interchangeably refer to firm accounts as prop-desks, or intermediaries, and customer accounts as clients. The first two columns of Panel A report the statistics for DIS-ALL, DIS-Firm and DIS-Custom, where DIS-ALL is an aggregate disagreement across both investor types. The mean values range between 0.17 and 0.28. The cross-sectional means and medians of these estimates are quite close, with the minimum values of 0 (no disagreement) and the maximum of 1.7, the highest level of disagreement.

The means of Customer and Firm order imbalances have opposite signs, for both calls and puts, and the absolute values of these numbers are economically significant. For example, Customer call imbalances are -7.1% on average versus Firm call order imbalances of 3.1%. For further comparison, the stock order imbalances, Panel B, are 0.6% on average. These results for net order flows are in lines to those reported in Goyenko (2015) and further support our approach of separately considering Customer and Firm disagreements.

Table 2 report the correlation matrix across all variables. The correlations are first computed across all firms by week, and then averaged across all weeks in our sample. Total disagreement (DIS-ALL) is highly correlated with DIS-Custom, 0.89, and less so with DIS-Firm, 0.43. The correlation between DIS-Firm and DIS-Custom is 0.36 which provides first evidence that while having a small degree of co-movement, these two investors' disagreements are quite different.

As far as relations between disagreement and options imbalances are concerned, we do not observe any significant correlations. The highest correlation is between DIS-Custom and IMB Call

Custom of 0.12, and DIS-Custom and IMB Put custom of 0.11. The correlations between firm disagreement and firm and customer order imbalances are lower. Call order imbalances are negatively correlated between customer and firm initiated trades, -0.35, and the correlation is similar for put order imbalances between customer and firm net order flows, -0.29.

Overall we conclude that two disagreement measures capture different information compared to all other control variables. In the next section we directly test the hypothesis of whether disagreement predicts stock returns.

IV. Stock Returns Predictability

IV.1 Cross-sectional Regressions

All tests in this section are weekly Fama and MacBeth (1973) cross-sectional regressions. Point estimates are first obtained from cross-sectional regressions by time and then all coefficients are averaged across all weeks in the sample. The t-statistics are computed using Newey and West (1987) error correction for autocorrelation with 3 lags.

The main regression model specification is

$$CAR_{i,t+m} = b_0 + b_1 DIS_{i,t} + b_2 PP_{i,t} + b_3 IMB\ Call_{i,t} + b_4 IMB\ Put_{i,t} + b_5\ OS_{i,t} + b_6\ ILS_{i,t} + b_7\ Size_{i,t} + b_8 StockIMB_{i,t} + b_{9-12} \sum_{t}^{t-4} R_{i,t} + b_{13}\sigma(R_{i,t}) + \varepsilon_0$$

where *m* is predictive horizon ranging from 1 to 3 weeks. *CAR* is a stock weekly cumulative abnormal return. The abnormal return is computed as the difference between individual stock return and CRSP value-weighted market index for each week. The regression also controls for stock characteristics such as relative effective spreads, *ILS*, size, stock order imbalances, 3 lags of stock returns, R_t, to control for possible price run ups, and squared stock return to proxy for volatility, $\sigma(R_t)$.

Table 3, Panel A, report first predictive regressions for DIS-ALL, DIS-Custom, and DIS-Firm, and only controlling for past price run ups, i.e. 3 lags of stock returns, R_t, and volatility, $\sigma(R_t)$. Interestingly, while using DIS-ALL, we find no significant predictability for next week stock returns. This is similar to the results of Ge, Lin and Pearson (2015) who also find no significant

predictability from disagreement to stock returns in their sample. However, disaggregating DIS-ALL into DIS-Custom and DIS-Firm provides the new insight about how disagreement affects asset prices. After controlling for pas returns and volatility, both DIS-Custom and DIS-Firm negatively and significantly predict next week stock returns. This is the first important result in this paper.

Given the evidence that net order flows between two investor types are highly negatively correlated, Table 2, we might also expect that their disagreements might be somewhat orthogonal as they disagree differently about different information. As such, an aggregate disagreement, DIS-ALL, might cancel out these two opposite effects and thus result in overall agreement. In the rest of the analysis we focus on understanding of the differences between DIS-Custom and DIS-Firm, and what information they capture for the future asset prices.

Table 3, Panel B, presents the results for multi-period forecasts and using all control variables for DIS-Firm, and DIS-Custom separately. Both, firm level and customer disagreements negatively and significantly predict next week abnormal returns even after controlling for *PP*, options and stock order imbalances, *OS*, and stock illiquidity.

Previous literature argues that *PP* and *OS* capture private information and therefore have predictive power for returns. In our sample, *PP* does negatively predict stock returns similar to the results in Pan and Poteshman (2006). The effect of *OS* on stock returns is insignificant, which can be explained by the results of Ge at al (2015) who reject information story explanation for *OS*.

Further, our results hold after controlling for options order imbalances. As argued previously in the literature, IMB Options also capture private information and thus predict stock returns (Hu (2014)). Our results also hold after controlling for stock order imbalances, which also have been shown to forecast stock returns (Kelley and Tetlock, 2013), and stock illiquidity. Customer disagreement remains a significant forecaster of stock returns up to three weeks ahead, and firm disagreement is up to two weeks ahead.

To decrease the effect of outliers on the coefficient estimates, similar to Ge, Lin and Pearson (2015) and Johnson and So (2012), in Panel C, we use portfolio decile ranking for each variable in the regression rather than using the raw values. Here all variables, except stock returns and volatilities, are first ranked in decile portfolios, and then, in the cross-sectional regressions we use the portfolio deciles ranks of these variables rather than their raw values. The results for our disagreement variables hold regardless whether we use raw estimates or portfolio ranks

regressions. Interestingly, in ranks regression, ILS is no longer significant. Its significant coefficient in Panel B can be attributed to collinearity due to its negative correlation with customer and firm disagreement measures, -0.23 and -0.14 respectively, Table 2.

Moreover, rank regressions, given that the coefficients have similar scales, allows comparing their economic magnitudes. Customer disagreement has the highest coefficients, -0.0002, compared to all other predictors, while firm disagreement becomes similar in economic impact to PP measure for week 2 forecast.

Overall, we conclude, that firm and customer disagreements robustly predict stock returns and in economic magnitudes their effect is comparable at least, and higher sometimes, compared to the effect of other predictors. Note that the other predictors are proxies for informed trading while our disagreement measure is capturing the dispersion of opinion. As such, our results show the importance of dispersion of opinion for asset pricing.

To understand further the economic magnitudes, Table 4 presents portfolio sorting results. Here, each week we sort stocks into quintile portfolios based on DIS-Firm (Panel A), or DIS-Custom (Panel B), or both (double-sorting, Panel C) in week t, and then compute average risk adjusted returns of this portfolios in weeks *t+1*, *t+2*, and *t+3* using Fama-French-Carhart risk factors. Panels A and B report portfolios Alphas, and the Alpha of a zero investment strategy portfolio of buying High and selling Low disagreement portfolios and unwinding the position in the one of subsequent weeks.

First, the portfolio risk-adjusted returns are monotonically decreasing with disagreement, which confirms the cross-sectional regressions results in Table 3. Second, the High minus Low strategies provide economically significant numbers of -5.7% per annum for firm disagreement (Panel A) and -4.4% per annum for customer disagreement (Panel B). Moreover, the economic magnitudes of these strategies persist for several weeks after portfolio formations.

Double-sorting portfolio results in Panel C provide insight on how two disagreement measures are different. Here, portfolios are formed first on sorting all stocks in portfolio quintiles by customer disagreement, and then each customer disagreement quintile is sorted into quintile portfolios based on firm disagreement in week *t*. Risk adjusted portfolio returns, and the returns on High minus Low strategies are reported in the table for week *t+1*. First, 5-1 strategy for Customer disagreement produces the highest and significant at the 10% level profit of -8% per annum for the 5^{th}, the highest, firm disagreement portfolio. Thus, Customer dispersion of opinion

is the highest when the firm dispersion of opinion is the highest too. However, the reverse is not true. The highest High-Low strategy Alpha of -12% per annum is observed for firm disagreement in the third (the most neutral) customer disagreement portfolio. This highlights the difference between two disagreements: firm or prop-desk tend to have dispersion of opinions on a different cross-section of stocks, compared to customer or client disagreement. The results overall call for further understanding what information these two investors type disagree about, and how it can be related to the existing literature on effect of disagreement on asset prices. We explore these questions in the next section using the novel news database.

IV. 2 News Indexes and Disagreement: Cross-Sectional Analysis

We obtain information on news from the RavenPack Analytics (RPA) DowJones and Press Release files. Both parts of the database include one file with equity news (EQ) and one file with global macro news (GM). The former includes firm-specific news stories about headlines such as news about earnings announcements, analyst estimates, credit ratings, product releases, business contracts, management changes, and M&A announcements, to name a few examples. The latter covers news about economic output, consumption, employment, foreign exchange and interest rates, credit, the balance of payments, production, and housing, amongst others.

RPA employs machine reading technology to convert unstructured news into a set of variables. These include scores which reflect whether the news is positive or negative, subject categories (such as ``dividend above expectations''), entities (such as a specific firm or country) that are affected by the news, as well as the relevance of a news headline for an entity.

We rely on RPA's Event Sentiment Score (ESS) for the construction of our news indexes. ESS combines various dictionary-based sentiment indicators with news-category specific sentiment as estimated by RPA analysts. It also captures quantitative information included in a news story such as for example a takeover premium paid in an M&A transaction. A single news headline can have different implications for the involved entities and the RPA database includes accordingly multiple entries per article. For instance, a news story about an acquisition produces separate entries for the acquirer and the target. As M&A news are typically substantially more

positive for the target, the ESS value is usually higher for the RPA entry related to the target than that of the acquirer. ESS values vary between zero and 100, with values below 50, equal to 50 and above 50 corresponding to negative, neutral, and positive news, respectively.

To avoid lagged repeated news, we restrict our analysis to novel news stories with an RPA novelty score equal to 100. Furthermore, we only use news stories which are highly relevant to a company as indicated by an RPA relevance score of 100. This is consistent with Von Beschewitz et al. (2015) who show that markets do not react to news with low relevance. Finally, we discard all ``ex-post'' news that are written about market movements, as opposed to fundamental ``ex-ante'' news that (may) cause market reactions. Accordingly, we filter out news about trading imbalances, insider trading, technical trading signals, and trading halts, amongst others.

For our firm-level analysis, we aggregate ESS from individual EQ news stories on a firm-trading-day level as follows. We first compute the average ESS of all news stories related to a specific firm and observed between the previous trading day's market close and the current trading day's close. News published during non-trading days are thus assigned to the next trading day. We then aggregate the firm-day values to weekly averages. Table A.1 in the Appendix provides summary of news categories, and their statistics for the sample of our firms. The highest frequency of news in our sample is attributed to the earnings announcements, followed by products and services news category, revenues, labor-issues, investor relations, marketing, and analyst ratings.

We obtain ESS News score for each firm per week. We next test whether our disagreement measures can predict the direction of future news. For example, Miller (1977) theory implies that the dispersion of opinions should be associated with over optimism in the market and thus we expect it to be positively associated with future positive news about firms. Table 5 reports weekly predictive results for News Scores, where all control variables are similar to those in Table 3. We run two regression specifications, first, without controlling for lagged news score, and the second include lagged News score to control for persistence in press releases. Panel A reports results for firm disagreement and Panel B for customer disagreement. Firm disagreement has no predictive effect on future news. It certainly rejects over-optimistic investor Miller (1997) hypothesis for prop-desk, since their dispersion of opinions cannot be linked to future positive information about firm level fundamentals. Note, that we measure the level of optimism with higher positivity of the news scores (above 50). In contrast, Customer disagreement positively and significantly predicts News, even after controlling for persistence in the News scores. This provides first evidence that

Miller (1977) theory holds for only one type of investor: client account driven dispersion in opinion.

Among other variables, *PP* negatively and consistently predicts News. As argued by Pan and Poteshman (2006), their measure is capturing negative information about firm fundamentals, and thus reflects investors' intentions to short-sell the underlying stocks in options market. The higher *PP* ratio in our regressions implies more negative News the following week, and thus is consistent with trading on negative information in options market. Neither options imbalance, nor OS, nor stock imbalances have significant predictability for the News.

Given the results above, the obvious question one can ask is how disagreement-News relationship is associated with future negative predictability for stock returns. In Table 6 we decompose disagreement conditioned on the direction of News. If the News score is above median value in our sample (above 52) we retain the disagreement value and name it DIS-Positive, and zero otherwise. If News score is below median value, the disagreement value for this firm-week is retained and we call it DIS-Negative, and zero otherwise. Thus, for each firm-week, for both customer and firm disagreement, we contemporaneously identify disagreements on only positive (DIS-CustomP, and DIS-FirmP) and only negative (DIS-CustomN, and DIS-FirmN) news, and then use them to predict stock returns.

Panel A report the results for firm disagreement. The first columns replicates the results of Table 3 for the cross-section of firms with news index available. For example, in Table 3 we have 745 and 1220 stocks per cross-section for firm and customer disagreement measures respectively. In Table 6 the respective averages per cross-section are 379 and 577. Although the News sample is smaller, the cross-section is large enough to obtain statistically valid results. The second regression uses positive and negative News firm disagreement. Here, we can see that predictability is driven by disagreement about Negative News, DIS-FirmN. The coefficient of disagreement on positive News, DIS-FirmP is statistically insignificant. Moreover, the difference between coefficient estimates of DIS-FirmN (negative News disagreement) and DIS-FirmP (positive news disagreement) is statistically significant.

The results are different in Panel B for customer disagreement. Here the first column replicates the results of Table 3 for sub-sample of firms with News index available. The second regression reports the results for positive (DIS-CustomP) and negative (DIS-CustomN) disagreements. Both negatively and statistically significantly predict next week abnormal stock

returns with very similar coefficients. The difference between coefficient estimates of DIS-CustomN and DIS-CustomP is statistically insignificant. Therefore, negative predictability of stock returns by customer disagreement is driven by over-optimism about both, negative and positive news. This supports over-optimistic investor Miller (1977) theory.

Unlike customer disagreement, firm disagreement predictability for stock returns is entirely attributed to dispersion of opinion about negative news only. Given that we associate the higher level of optimist with higher positivity of News score, we cannot link firm disagreement to over-optimism.

Disagreement about negative firm fundamentals can be attributed to either firm specific negative news, or negative market/macro-economic news which negative firm specific news might be reflecting in our cross-sectional tests. Essentially, this is the news about either negative cash flows or anticipation of changes in interest rates which macro-economic news can be capturing. Monetary policy literature largely concludes that increases in interest rates have negative impact on financial markets. We therefore evoke to the aggregate, market-wide analyses to differentiate which effect dominates.

We construct two aggregate News indexes. First, we aggregate the weekly ESS News scores across all stocks by calculating the market value-weighted average Index, News-Firm. Given the content of news (Table A.1) this index incorporates largely information about cash flows.

Second, we compute a US macro news index (News-Macro) from the RPA GM files as the average ESS score of all GM news stories on a given week. Table A.2 in Appendix provides descriptive statistics of the score averages and frequencies of each news item which we include in the construction of the index. The highest frequency of news is attributed to the announcements about balance of payments, followed by consumption, foreign exchange, employment, credit ratings, GDP growth and etc. Note that all these data are taken into account by regulators to manage interest rate policy. Therefore this News Index, while capturing an aggregate macro-stability, also may reflect the future direction or market anticipation of future direction of monetary policy.

We also aggregate disagreement measures across stocks, and in the next section we explore market-wide applications of these measures and their relations with aggregated News indexes and common market sentiment indexes. Moreover, given the cross-sectional evidence on stock return predictability we also hypothesize that our disagreement measure can have predictive power for

an aggregate market return, and risk. More specifically, since customer disagreement is largely attributed to over-optimism, we expect it to be positively related to future volatility, and also positively predict an aggregate cash flow based News index, and other sentiment indexes used in the literature. If firm disagreement is attributed to the uncertainty about future monetary policy, or overall macro-uncertainty, we expect it to negatively predict an aggregate market return.

V. Market-Wide Disagreement, Return, Volatility and News Indexes

V.1 Does Market-Wide Disagreement Predict Aggregate Expected Return and Variance?

To examine whether aggregate client and intermediary (prop-desks) disagreement measures can predict market return and variance, we use the standard predictive Vector Autoregressive approach (VAR). This allows us to quantify the impact the two variables of disagreement have on the joint dynamics of market return and variance allowing for auto-correlation and cotemporaneous cross-correlation. VAR models have been used in numerous empirical studies including Carlin, Longstaff, and Matoba (2014) who also investigate the pricing implications of disagreement.

Consistent with our previous analysis, we adopt weekly frequency. Recall that disagreement is measured at the firm-level. In order to obtain aggregate client and intermediary disagreements, we compute the equally-weighted daily average of the two measures across all stocks in our sample. We then average the daily measures per week to get one single weekly client and intermediary disagreement.

The market return is weekly returns of the S&P 500 index. Following Ang, Hodrick, Xing, and Zhang (2006) among many others, we use the VIX index to capture fluctuations in market variance and average VIX daily changes for each week.

To account for the effect of market-wide news on aggregate market return, aggregate variance, and market-wide disagreements, we use interchangeably the two indices, News-Firm and News-Macro.

Based on these five variables, we estimate the following VAR model

$$X_t = \alpha + AX_{t-1} + \varepsilon_t,$$

where X_t is a 5 by 1 vector of dependent variables, α is a 5 by 1 vector capturing the intercept, A is a 5 by 5 matrix of causal parameters for which $A(n,m)$ refers to the parameter located in row n of column m, and ε_t is a 5 by 1 vectors of innovations which can be contemporaneously cross-correlated. We estimate two versions of this model depending on the news index used. More precisely, we define the dependent variable X_t in each specification as

$$X_t = \begin{bmatrix} S\&P\ 500\ Ret \\ \Delta Vix \\ News\ Index \\ DIS\ Client \\ DIS\ Inter. \end{bmatrix}_t$$

for which $News\ Index$ corresponds to the aggregate equity news index, News-Firm, in the first specification and is set to the US macro news, News-Macro, in the second. Note that $ews\ Index$, $DIS\ Client$, and $DIS\ Inter$. have all been demeaned and that the model is estimated by maximum-likelihood. Figure 1 presents Customer (Client) and Firm (Intermediary) aggregate disagreements graphs. The correlation between the two series is low, -0.07, confirming that they are capturing different information. Figure 2 presents the graphs for News-Firm and News-Macro indexes. Here too, the two series are not related with the correlation of -0.01.

Table 7 presents the estimation results. Panel A reports the parameter estimates and t-statistics when the news index is set to aggregate equity news, News-Firm. Panel B presents the results when we use US macro news, News-Macro. A few interesting patterns emerge. In Panel A.1 and Panel B.1 both lagged client and intermediary disagreements are associated with lower next period S&P 500 returns independently of the news index. However, only the coefficient estimate for intermediary disagreement is statistically significant across the two VAR specifications. The Newey-West p-value corrected for 3 auto-correlation lags obtained for $A(1,5)$ (i.e. parameter capturing the causal impact of intermediary disagreement on S&P 500 returns) is 0.031 in Panel A and is 0.029 in Panel B. The economic impact of intermediary disagreement on next period market returns is substantial. Based on the Panel A, a one standard deviation increase in intermediary disagreement results in 11.76% annual decrease in next period market returns (i.e. -0.0843* STD($DIS\ Inter.$)*52*100). This is consistent with the cross-sectional finding documented in the previous section. Because intermediaries disagreement increases with more

negative news, a high intermediary disagreement is subsequently followed by lower expected market return all things being equal.

In aggregate, intermediary and client disagreements have different pricing implications. In Panel A.1 and Panel B.1 only market-wide client disagreement predicts next period market volatility. The coefficient $A(2,4)$ (i.e. parameter capturing the causal impact of client disagreement on VIX) is 0.0180 in Panel A.1, and 0.0174 in Panel B.1. The Newey-West p-value of this coefficient ranges from 0.0145 to 0.0240 across the two specifications. The economic impact of client disagreement on volatility is large. Based on the coefficient in Panel A, a one standard deviation increase in client disagreement is followed by a 0.50% annual increase in VIX (i.e. 0.018*STD($DIS\ Client$)*STD(52)*100). This is more than thirteen times bigger than the average annual change in VIX in our sample. Unlike intermediaries, clients disagree equally about good and bad news. More news contemporaneously result in higher client disagreement on aggregate implying a higher divergence in trading which ultimately leads to an increase in market volatility in the next period.

While most of the empirical disagreement literature uses proxy for disagreement as given and study its impact on asset values, very few papers try to understand the sources and dynamics of disagreement across different type of investors. In this regard, Table 7 can be used to better understand the joint dynamic of intermediary and client disagreements on aggregate and its relation to information flow. First, we see that disagreement is persistent over time (see $A(4,4)$ in Panel A.2 and B.2 for DIS-Client, and $A(5,5)$ in Panel A.3 and B.3 for DIS-Intermediaries). Both are quite persistent with client disagreement being more persistent than intermediary disagreement. This justifies the use of VAR analysis which also corrects for the lagged effects of all endogenous variables. Further, a lead-lag relationship between intermediary and client disagreement is readily apparent from Panel A.2, A.3, B.2, and B.3. Higher intermediary disagreement implies a lower subsequent client disagreement, and in turn, a higher client disagreement results in a lower intermediary disagreement in the next period. Further, consistent with the persistency of disagreements, From Panel A.2 and B.2 we see that news is somewhat persistent. Good (resp. bad) news in one period is more likely to be followed by other good (i.e. bad) news in the next period.

In Panels A.2 and B.2, customer disagreement does not depend on lagged equity or macro news index. While equity News index does not significantly affect firm disagreement, Panel A.3,

macro-economic news index significantly negatively predicts disagreement of financial intermediaries. More positive macro-News decrease firm disagreement, and more negative macro-economic outlook news increase firm disagreement. This in turn helps explain the source of disagreement among financial intermediaries: the negative macro-economic outlook. Macro-economic news can be used to interpret future directions of monetary policy, and thus the interest rate regime, and uncertainty about future growth. As such the disagreement of financial intermediaries can be capturing market reflection of professional investors about macro-economic uncertainty.

Previous analysis underlines the relations between disagreement and news. Because news also influence investor sentiment, we now analyze the dependence of disagreements on common sentiment indexes.

V.2 Disagreement and Market-Wide Investor Sentiment

We study the joint dynamic of client and intermediary disagreement and investor sentiment. Similarly to previous section, we use a VAR model to study the interdependence of these three variables.

To capture investor sentiment, we use two different proxies. The first is the University of Michigan's consumer sentiment index. The second is Baker and Wurgler (2006)'s sentiment index that we obtain from Jeffrey Wurgler's personal webpage. Figure 3 presents time series graphs of these indexes. These indexes have been used extensively to proxy investors/consumers sentiment about future economic outlook (see, among others, Carroll, Fuhrer, and Wilcox, 1994; Baker and Wurgler, 2006; and Lemmon and Portniaguina, 2006). Note that both indexes are constructed monthly. Consequently, we construct monthly measures of intermediary and client disagreement by first averaging the stock-level disagreements daily, and then average the daily aggregate disagreement measures over each month.[4]

[4] Our goal here is to shed light on the possible interaction of disagreement and sentiment. Using monthly data reduces considerably the number of observations available to estimate the VAR. Thus, we restrict our analysis to modelling the joint dynamic of intermediary disagreement, client disagreement, and sentiment without accounting for market return and variance. Note that the results we present in this section are not quantitatively sensitive to

Table 8 reports the results for the tri-variate VAR. As in Table 7, we split the results in two distinct Panels. In Panel A, the sentiment index is set to the Michigan consumers' index. In Panel B, we use Baker and Wurgler's index to proxy investors' sentiment. Panel A uncovers another distinction between intermediary and client disagreement. A high client disagreement is associated with a high sentiment in the next period while a high intermediary disagreement translates into a low subsequent sentiment. Note that $A(1,2)$'s Newey-West p-value adjusted for 3 auto-correlation lags is 0.057 and the p-value obtained for $A(1,3)$ is 0.

Using Baker and Wurgler's index, Panel B, the above results hold only for customer disagreement, i.e. Customer disagreement consistently positively predict both sentiment indexes, and the reverse is not true. It suggests that customer disagreement by itself can be a proxy for future investors' sentiment.

Firm level disagreement negatively predicts the Michigan consumers' index, while the sentiment indexes positively predict firm disagreement. Negative predictability of consumer sentiment by firm disagreement is consistent with its negative predictability for aggregate market returns.

5. Conclusion.

Disagreement and its effect on asset prices has been debated in the literature for a long time starting from Miller (1977). However, to the date, the literature still has struggled to measure disagreement on the individual stock or market-wide levels, and come to unanimous empirical conclusions of how dispersion of opinions should affect asset prices.

Availability of singed trading volume data in options market originated exclusively from investors and reflecting their synthetic long or short stakes in the underlying stocks present a unique opportunity to identify disagreement based on investors' trades. This is much different from all previous disagreement measures inferred from analyst forecasts dispersion which have very little to do with how actual investors think/trade.

the inclusion of these variables. However, the statistical significance of the coefficients decreases as we increase the number of dependent variables as more parameters need to be estimated.

We contribute to the literature in several important ways. First we find that two investor types, customer (client) and firm (intermediary such as prop-desks), have different sources of their disagreement. Customer driven disagreement and its negative predictive effect on stock returns is consistent with Miller (1977) theory. Higher dispersion of opinions among customer accounts positively predicts common sentiment indexes and overall is associated with higher optimism. While aggregated on the market level, customer disagreement positively predicts market wide volatility (VIX).

Second, firm or prop-desks disagreement is not consistent with investor's' optimism. Here the dispersion of opinions increases after negative macro-economic news, and it negatively predicts cross-section of stock returns and an aggregate market index. This type of disagreement can be associated with the rational expectation theory providing that the source of asymmetric information is monetary policy uncertainty. As such, the negative predictive effect of pro-desks disagreement on stock returns is overall consistent with the effect of monetary policy on financial markets.

Finally, we suggest two market wide indexes. First, is client based disagreement which reflect market sentiment/optimism. The advantage of this index that it is trade driven, is available at higher frequencies than monthly (daily or weekly), and it also predicts all other know sentiment indexes. Second is the firm disagreement which is the measure of macro-economic uncertainty. To the date there is no measure of uncertainty which has been shown in the literature to have a different impact on stock returns compared to the risk. We thus propose the first index of uncertainty.

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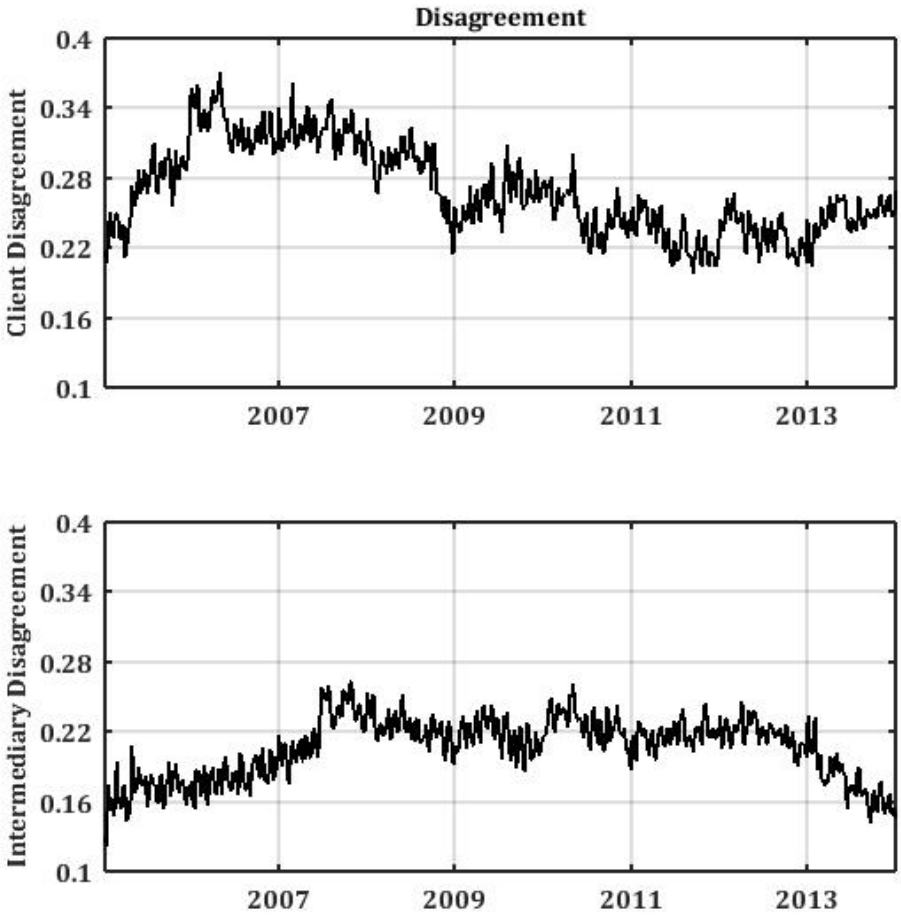
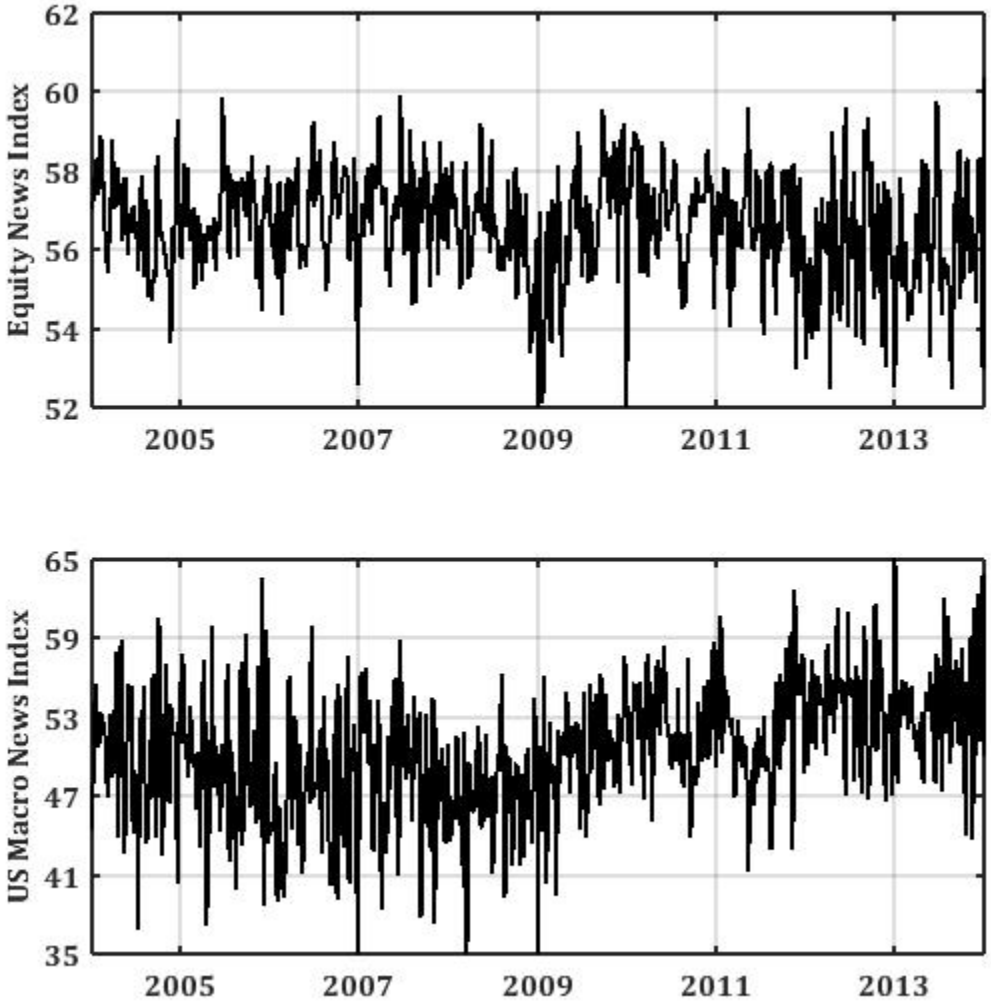
Figure 1: Time-series of Client and Intermediary Disagreement



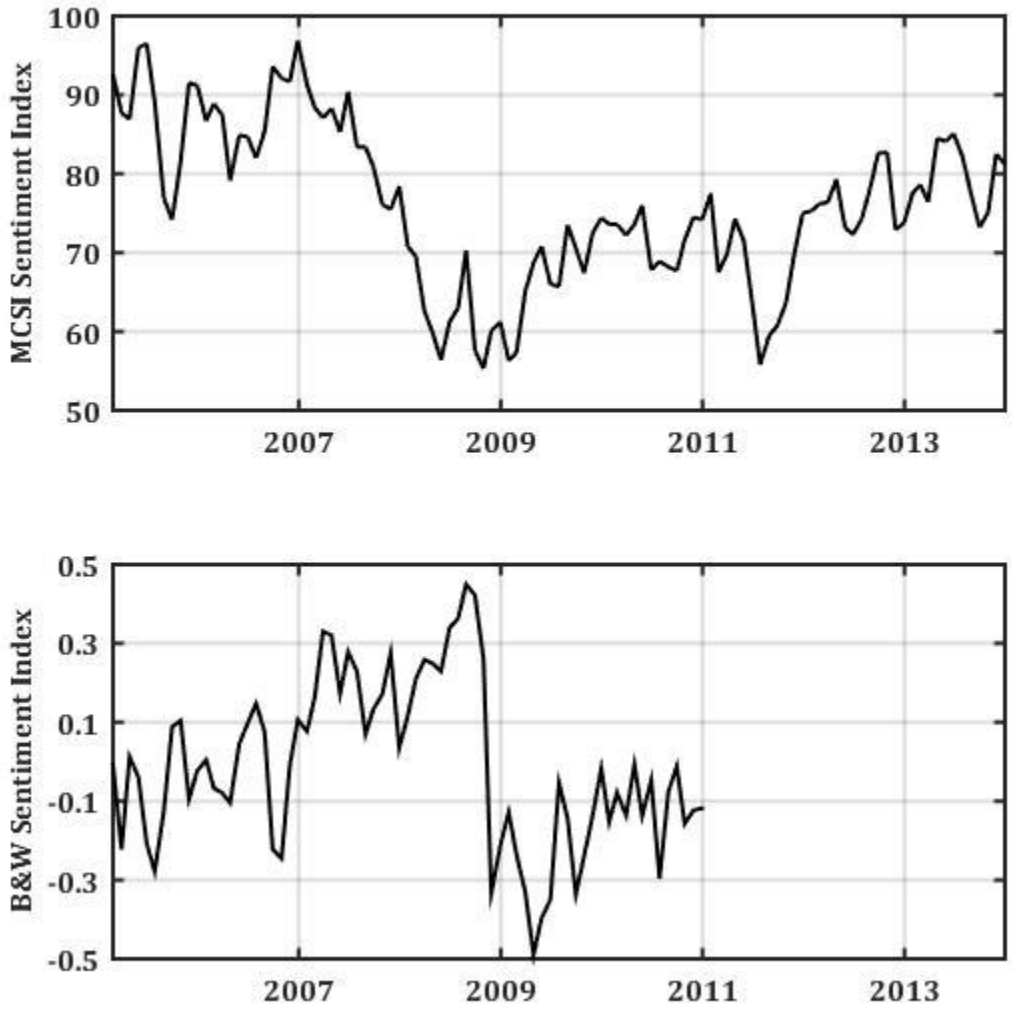
Note to Figure: We plot the time-series of weekly client and intermediary disagreement. The sample period is from January 2005 to December 2013.

Figure 2: Time-series of Aggregate Equity News Index and US Macro News Index



Note to Figure: We plot the weekly time-series of aggregate equity news and US macro news. The sample period is from January 2005 to December 2013.

Figure 3: Time-series of Michigan Consumer Sentiment Index (MCSI) and Baker and Wurgler (2006)'s Sentiment Index



Note to Figure: We plot the monthly time-series of Michigan Consumer Sentiment Index (MCSI) and Baker and Wurgler (2006)'s Sentiment Index. The sample period is from February 2005 to December 2013 for top panel and from February 2005 to December 2010 for the bottom panel.

Table 1. Summary statistics

The table presents summary statistics for weekly options customer and firm disagreement measures (DIS-Custom, DIS-Firm) and aggregate disagreement among two investor types, DIS-ALL, options imbalances(*IMB*) for calls, puts, originated by customer and firm accounts (IMB Call Custom/Firm, IMB Put Custom/Firm), stock (*StockIMB*) order imbalances. Options imbalances and disagreements are computed using signed open/close, buy/sell CBOE/ISE data. The imbalances and disagreements are computed first on options series level and then aggregated across series on a firm level. Stock imbalances are computed using TAQ data and defined as buy volume less sell volume divided by the sum of buy and sell volumes. The intraday volume is signed using Lee and Ready (1991) algorithm and then aggregated on daily level for each firm. Options volume is measured in number of contracts, while stock volume is measured in number of shares traded. *ILS* is stock dollar-volume weighted effective spreads computed for each week using intraday TAQ data. *PP* is Pan and Poteshman (2006) put to call volume ratio, and *OS* is Johnson and So (2012) options to stock volume ratio. The sample period is from January 2005 to December 2015.

Panel A. Disagreement and Imbalances

	DIS-ALL	DIS-Firm$_{i,t}$	DIS-Custom$_{i,t}$	IMB Call Customi,t	IMB Call Firmi,t	IMB Put Customi,t	IMB Put Firmi,t
Mean	0.282	0.171	0.231	-0.071	0.031	-0.079	0.041
StDev	0.203	0.169	0.195	0.257	0.334	0.250	0.299
Median	0.272	0.139	0.204	-0.066	0.037	-0.068	0.040
Min	0	0	0	-0.979	-0.980	-0.979	-0.979
Max	1.674	1.469	1.595	0.980	0.980	0.979	0.980

Panel B. Other Control Variables

	PPi,t	OSi,t	ILS i,t	StockIMB i,t
Mean	0.314	5.222	0.002	0.006
StDev	0.302	0.194	0.004	0.102
Median	0.257	5.249	0.001	0.003
Min	0	-9.030	0	-1
Max	1	6.668	0.486	1

Table 2 Correlation Matrix.

The table presents correlation matrix of all economic variables. The correlations are computed across firms per week and then time series averages are reported in the table. We use options customer and firm disagreement measures (DIS-Custom, DIS-Firm) and aggregate disagreement among two investor types, DIS-ALL, options imbalances(*IMB*) for calls, puts, originated by customer and firm accounts (IMB Call Custom/Firm, IMB Put Custom/Firm), stock (*StockIMB*) order imbalances. Options imbalances and disagreements are computed using signed open/close, buy/sell CBOE/ISE data. The imbalances and disagreements are computed first on options series level and then aggregated across series on a firm level. Stock imbalances are computed using TAQ data and defined as buy volume less sell volume divided by the sum of buy and sell volumes. The intraday volume is signed using Lee and Ready (1991) algorithm and then aggregated on daily level for each firm. Options volume is measured in number of contracts, while stock volume is measured in number of shares traded. *ILS* is stock dollar-volume weighted effective spreads computed for each week using intraday TAQ data. *PP* is Pan and Poteshman (2006) put to call volume ratio, and *OS* is Johnson and So (2012) options to stock volume ratio. The sample period is from January 2005 to December 2015.

	DIS-ALL	DIS-Firm$_{i,t}$	DIS-Custom$_{i,t}$	IMB Call Customi,t	IMB Call Firmi,t	IMB Put Customi	IMB Put Firmi,t	PPi,t	OSi,t	ILS i,t
DIS-ALL										
DIS-Firm$_{i,t}$	0.426									
DIS-Custom$_{i,t}$	0.886	0.358								
IMB Call Customi,t	0.108	0.070	0.124							
IMB Call Firmi,t	-0.003	-0.031	-0.049	-0.351						
IMB Put Customi,t	0.097	0.071	0.113	-0.027	0.010					
IMB Put Firmi,t	0.022	-0.055	-0.032	-0.017	0.226	-0.290				
PPi,t	0.068	0.049	0.065	-0.322	0.060	0.399	-0.112			
OSi,t	0.052	0.000	0.053	0.026	-0.011	-0.009	0.002	-0.031		
ILS i,t	-0.224	-0.136	-0.232	0.084	-0.048	-0.124	0.074	-0.231	0.031	
StockIMB i,t	0.034	0.003	0.033	-0.045	0.032	0.047	-0.014	0.026	-0.006	-0.133

Table 3. Cross-Sectional Regressions.

The table presents predictive cross-sectional regressions results for abnormal weekly stock returns CAR (t+1) by disagreement type. The independent variables are options customer and firm disagreement measures (DIS-Custom, DIS-Firm) and aggregate disagreement among two investor types, DIS-ALL, options imbalances(*IMB*) for calls, puts, originated by customer and firm accounts (IMB Call Custom/Firm, IMB Put Custom/Firm), stock (*StockIMB*) order imbalances. Options imbalances and disagreements are computed using signed open/close, buy/sell CBOE/ISE data. The imbalances and disagreements are computed first on options series level and then aggregated across series on a firm level. Stock imbalances are computed using TAQ data and defined as buy volume less sell volume divided by the sum of buy and sell volumes. The intraday volume is signed using Lee and Ready (1991) algorithm and then aggregated on daily level for each firm. Options volume is measured in number of contracts, while stock volume is measured in number of shares traded. *ILS* is stock dollar-volume weighted effective spreads computed for each week using intraday TAQ data. *PP* is Pan and Poteshman (2006) put to call volume ratio, and *OS* is Johnson and So (2012) options to stock volume ratio. R_i is return on a stock, and σ(*Ret*) is a proxy for stock volatility computed as a squared stock return. The sample period is from January 2005 to December 2015.

Panel A. Weekly Cross-Sectional Regressions

	$CAR_{i,t+1}$	t-stat		$CAR_{i,t+1}$	t-stat		$CAR_{i,t+1}$	t-stat
$DIS\text{-}ALL_{i,t}$	-0.0008	-1.21	$DIS\text{-}Custom_{i,t}$	-0.0015	-2.08	$DIS\text{-}Firm_{i,t}$	-0.0015	-2.21
$R_{i,t}$	-0.018	-4.14	$R_{i,t}$	-0.018	-4.11	$R_{i,t}$	-0.014	-2.81
$R_{i,t-1}$	-0.004	-1.17	$R_{i,t-1}$	-0.004	-1.13	$R_{i,t-1}$	-0.003	-0.73
$R_{i,t-2}$	-0.001	-0.33	$R_{i,t-2}$	-0.001	-0.34	$R_{i,t-2}$	-0.003	-0.62
$R_{i,t-3}$	0.003	0.91	$R_{i,t-3}$	0.003	0.86	$R_{i,t-3}$	0.002	0.61
$\sigma(Ret_i)$	0.098	3.21	$\sigma(Ret_i)$	0.098	3.22	$\sigma(Ret_i)$	0.046	1.47
Adj. R^2	0.096		Adj. R^2	0.097		Adj. R^2	0.114	
Avg. # stocks	1607		Avg. # stocks	1594		Avg. # stocks	762	

Panel B. Weekly Cross-Sectional Regressions: Multiperiod with Control Variables

	$CAR_{i,t+1}$	t-stat	$CAR_{i,t+2}$	t-stat	$CAR_{i,t+3}$	t-stat		$CAR_{i,t+1}$	t-stat	$CAR_{i,t+2}$	t-stat	$CAR_{i,t+3}$	t-stat
$DIS\text{-}Firm_{i,t}$	-0.0022	-2.81	-0.0020	-2.76	-0.0004	-0.57	$DIS\text{-}Custom_{i,t}$	-0.0034	-4.19	-0.0024	-2.36	-0.0023	-2.57
PPi,t	-0.0029	-4.35	-0.0016	-2.4	-0.0013	-2.03	PPi,t	-0.0017	-3.29	-0.0012	-2.33	-0.0006	-1.07
IMB Call Firmi,t	-0.0009	-2.36	-0.0008	-2.15	0.0001	0.25	IMB Call Customi,t	0.0035	7.97	0.0009	1.87	0.0011	2.62
IMB Put Firmi,t	0.0005	1.14	0.0003	0.82	-0.0002	-0.5	IMB Put Customi,t	-0.0011	-2.74	-0.0015	-3.57	-0.0006	-1.67
OSi,t	0.0006	0.25	-0.0002	-0.11	-0.0005	-0.27	OSi,t	0.0020	1.09	-0.0002	-0.14	0.0005	0.31
ILS i,t	-1.0569	-2.81	-0.9654	-2.66	-0.9783	-2.84	ILS i,t	-0.8089	-3.19	-0.6465	-2.62	-0.6822	-2.87
Size i,t	0.0000	-0.42	0.0000	-0.8	0.0000	-0.99	Size i,t	0.0000	-0.28	0.0000	-0.31	0.0000	-0.37
StockIMB i,t	0.0036	1.55	0.0057	2.64	0.0000	0	StockIMB i,t	0.0027	1.49	0.0036	2.23	0.0019	1.25
$R_{i,t}$	-0.010	-1.83	0.003	0.55	0.001	0.17	$R_{i,t}$	-0.007	-1.31	-0.002	-0.35	0.001	0.18
$R_{i,t-1}$	-0.002	-0.39	-0.002	-0.41	0.005	1.02	$R_{i,t-1}$	0.000	-0.05	-0.002	-0.52	0.003	0.62
$R_{i,t-2}$	0.000	-0.09	0.001	0.26	-0.001	-0.25	$R_{i,t-2}$	0.000	0.06	0.003	0.65	-0.003	-0.8
$R_{i,t-3}$	0.001	0.24	-0.005	-1.08	-0.001	-0.23	$R_{i,t-3}$	0.002	0.57	-0.002	-0.49	-0.001	-0.22
$\sigma(Ret_i)$	-0.017	-0.78	-0.042	-2	0.001	0.04	$\sigma(Ret_i)$	-0.011	-0.65	-0.027	-1.72	-0.013	-0.88
Adj. R^2	0.064		0.059		0.059		Adj. R^2	0.052		0.049		0.048	
Avg. # stocks	745						Avg. # stocks	1220					

Panel C. Weekly Cross-Sectional Regressions in Decile Ranks

	$CAR_{i,t+1}$	t-stat	$CAR_{i,t+2}$	t-stat	$CAR_{i,t+3}$	t-stat		$CAR_{i,t+1}$	t-stat	$CAR_{i,t+2}$	t-stat	$CAR_{i,t+3}$	t-stat
$DIS\text{-}FirmRank_{i,t}$	-0.0001	-3.17	-0.0001	-3.15	-0.0001	-1.63	$DIS\text{-}CustomRank_{i,t}$	-0.0002	-3.74	-0.0002	-2.42	-0.0002	-2.81
PPRanki,t	-0.0003	-4.25	-0.0001	-2.08	-0.0001	-1.81	PPRanki,t	-0.0001	-2.47	-0.0001	-1.95	0.0000	-0.45
IMB Call FirmRanki,t	-0.0001	-2.01	-0.0001	-2.03	0.0000	-0.12	IMB Call CustomRanki,t	0.0003	8	0.0001	1.96	0.0001	2.42
IMB Put FirmRanki,t	0.0001	1.27	0.0000	0.88	0.0000	-0.27	IMB Put CustomRanki,t	-0.0001	-3.54	-0.0001	-3.35	-0.0001	-2.12
OSRanki,t	0.0000	-0.16	0.0000	0.71	0.0000	0.18	OSRanki,t	0.0000	0.25	0.0000	0.05	0.0000	-0.03
ILS Rank i,t	-0.0002	-1.46	-0.0001	-0.82	-0.0001	-0.81	ILS Rank i,t	-0.0002	-1.33	-0.0001	-0.7	-0.0001	-0.74
Size Rank i,t	0.0001	0.59	0.0001	0.7	0.0001	1.27	Size Rank i,t	0.0001	0.68	0.0001	1.3	0.0001	1.43
StockIMB Rank i,t	0.0001	1.8	0.0001	2.34	0.0000	-0.03	StockIMB Rank i,t	0.0001	2.28	0.0001	2.09	0.0000	1.2
$R_{i,t}$	-0.009	-1.68	0.003	0.75	0.001	0.29	$R_{i,t}$	-0.005	-1.07	-0.001	-0.21	0.001	0.28
$R_{i,t-1}$	-0.002	-0.45	-0.002	-0.45	0.004	0.96	$R_{i,t-1}$	0.000	0.06	-0.002	-0.52	0.003	0.73
$R_{i,t-2}$	-0.001	-0.18	0.000	0.04	-0.002	-0.4	$R_{i,t-2}$	0.000	0.13	0.003	0.81	-0.004	-0.88
$R_{i,t-3}$	0.000	0.08	-0.005	-1.07	0.000	-0.07	$R_{i,t-3}$	0.003	0.7	-0.003	-0.63	-0.001	-0.18
$\sigma(Ret_i)$	-0.024	-1.09	-0.044	-2.11	-0.001	-0.07	$\sigma(Ret_i)$	-0.018	-1.08	-0.029	-1.82	-0.016	-1.06
Adj. R^2	0.068		0.064		0.064		Adj. R^2	0.057		0.053		0.053	
Avg. # stocks	745						Avg. # stocks	1220					

Table 4. Portfolio Sorting

The table presents equally-weighted portfolio quintiles alphas, where portfolios are sorted every week t based on *Customer or Firm Disagreement or both*, and then abnormal returns are computed for each portfolio the following week, *t+1*, using Fama-French-Carhart factors. The time period is from January 2005 to December 2013. t-statistics are based on Newey-West autocorrelation adjusted standard errors with 3 lags.

Panel A. Firm DIS Sorted Equally-weighted portfolios

portfolio	$Alpha_{t+1}$	t-stat	$Alpha_{t+2}$	t-stat	$Alpha_{t+3}$	t-stat
Low	13.377	1.56	12.956	1.59	13.264	1.6
2	12.946	1.52	11.124	1.44	10.620	1.31
3	12.439	1.44	10.664	1.39	11.938	1.46
4	11.926	1.41	10.343	1.35	11.511	1.45
High	7.360	0.86	8.192	1.05	11.318	1.35
High-Low	-5.744	-3.35	-4.780	-2.56	-1.793	-1

Panel B. Custom DIS Sorted Equally-weighted portfolios

portfolio	$Alpha_{t+1}$	t-stat	$Alpha_{t+2}$	t-stat	$Alpha_{t+3}$	t-stat
Low	14.398	1.62	13.906	1.67	14.491	1.64
2	14.143	1.61	12.607	1.54	15.045	1.76
3	13.429	1.55	12.695	1.57	12.757	1.51
4	10.979	1.29	10.792	1.38	13.630	1.67
High	10.003	1.15	9.548	1.2	10.134	1.22
High-Low	-4.396	-1.91	-4.358	-1.98	-4.357	-1.9

Panel C. Double-Sorted on DIS Firm and DIS Custom Equally-weighted portfolios

	1.DIS Custom	2	3	4	5.DIS Custom	5-1	t-stat
1.DIS Firm	16.532	13.696	15.190	9.949	10.459	-5.380	-1.630
2	14.825	17.173	11.043	10.368	13.361	-2.964	-0.570
3	12.572	12.499	10.062	13.351	11.759	0.251	0.070
4	16.249	7.934	12.263	13.145	11.240	-6.699	-1.530
5.DIS Firm	12.921	10.207	4.169	8.054	3.611	-7.913	-1.950
5-1	-4.833	-3.830	-11.822	-2.320	-6.672		
t-stat	-1.630	-1.130	-3.310	-0.620	-1.640		

Table 5. Predictive Regressions for News Indexes.

ESS is the news index obtained from the RavenPack Analytics (RPA) Dow Jones and Press Release files. It varies between zero and 100, with values below 50, equal to 50 and above 50 corresponding to negative, neutral, and positive news, respectively. The rest of variables is as described in Table 3.

Panel A. Weekly Cross-Sectional Regressions, Firm DIS

	$ESS_{i,t+1}$	t-stat	$ESS_{i,t+1}$	t-stat
$ESS_{i,t}$			0.098724	20.94
DIS-$Firm_{i,t}$	0.0224	0.11	-0.2547	-0.84
IMB Call Firmi,t	-0.0781	-0.64	-0.1043	-0.53
IMB Put Firmi,t	-0.1334	-1.13	-0.2613	-1.36
PPi,t	-1.5269	-9.01	-1.5648	-6.82
OSi,t	-1.0995	-2.14	-0.9414	-1.11
ILS i,t	-871.9540	-14.24	-969.9680	-10.85
Size i,t	0.0000	11.33	0.0000	7.92
StockIMB i,t	0.6277	1.16	-0.0498	-0.07
$R_{i,t}$	4.104	4.16	0.913	0.66
$R_{i,t-1}$	0.586	0.76	1.928	1.58
$R_{i,t-2}$	-0.007	-0.01	0.930	0.77
$R_{i,t-3}$	1.638	2.09	1.202	0.88
$\sigma(Ret_i)$	-37.324	-6.74	-32.091	-2.94
Adj. R^2	0.020		0.037	
Avg. # stocks	379		230	

Panel B. Weekly Cross-Sectional Regressions, Custom DIS

	$ESS_{i,t+1}$	t-stat	$ESS_{i,t+1}$	t-stat
$ESS_{i,t}$			0.107841	25.52
DIS-$Custom_{i,t}$	0.7264	4.39	0.3937	1.77
IMB Call Customi,t	0.2312	1.71	0.1658	0.75
IMB Put Customi,t	0.1605	1.21	-0.0574	-0.28
PPi,t	-1.1611	-9.91	-1.2206	-7.77
OSi,t	-0.4979	-1.4	-0.5013	-0.78
ILS i,t	-487.0480	-13.99	-627.0890	-11.69
Size i,t	0.0000	12.85	0.0000	9.54
StockIMB i,t	-0.1684	-0.41	-0.0401	-0.07
$R_{i,t}$	4.795	6.28	1.542	1.5
$R_{i,t-1}$	0.681	1.09	0.994	1.15
$R_{i,t-2}$	0.589	0.95	1.192	1.35
$R_{i,t-3}$	1.971	3.44	2.118	2.67
$\sigma(Ret_i)$	-34.069	-7.78	-25.005	-2.06
Adj. R^2	0.018		0.036	
Avg. # stocks	577		321	

Table 6. Return Predictability, Positive and Negative News Disagreement.

ESS is the news index obtained from the RavenPack Analytics (RPA) DowJones and Press Release files. It varies between zero and 100, with values below 50, equal to 50 and above 50 corresponding to negative, neutral, and positive news, respectively. If the News score is above median value in our sample (above 52) we assign disagreement value to DIS-Positive, and zero otherwise, and if News score is below median value, the disagreement value for this firm-week is assigned to DIS-Negative value and zero otherwise. The rest of variables is as described in Table 3.

Panel A. Weekly Cross-Sectional Regressions, Firm DIS

	$CAR_{i,t+1}$	t-stat	$CAR_{i,t+1}$	t-stat
$ESS_{i,t}$	0.000006028	0.39	-0.00000482	-0.27
DIS-$Firm_{i,t}$	-0.0025	-2.64		
DIS-$FirmP_{i,t}$			-0.00163	-1.62
DIS-$FirmN_{i,t}$			-0.00383	-3
IMB Call Firmi,t	-0.0010	-1.8	-0.00101	-1.79
IMB Put Firmi,t	0.0004	0.59	0.000313	0.52
PPi,t	-0.0025	-3.21	-0.00249	-3.25
OSi,t	0.0012	0.39	0.001125	0.38
ILS i,t	-0.7976	-1.68	-0.79039	-1.66
Size i,t	0.0000	-0.02	-1.05E-12	-0.25
StockIMB i,t	0.0046	1.52	0.004838	1.59
$R_{i,t}$	-0.011	-1.99	-0.01125	-2.03
$R_{i,t-1}$	-0.005	-0.86	-0.00512	-0.86
$R_{i,t-2}$	0.002	0.43	0.002298	0.41
$R_{i,t-3}$	0.000	0.03	0.000286	0.05
$\sigma(Ret_i)$	0.025	0.87	0.023894	0.84
Adj. R^2	0.078		0.077594	
Avg. # stocks	395		395	

Panel B. Weekly Cross-Sectional Regressions, CUSTOM DIS

	$CAR_{i,t+1}$	t-stat	$CAR_{i,t+1}$	t-stat
$ESS_{i,t}$	0.00001	0.74	0.000006494	0.39
DIS-$Custom_{i,t}$	-0.0038	-3.58		
DIS-$CustomP_{i,t}$			-0.0036	-3.37
DIS-$CustomN_{i,t}$			-0.0041	-3.4
IMB Call Customi,t	0.0037	5.68	0.0037	5.64
IMB Put Customi,t	0.0001	0.21	0.0001	0.19
PPi,t	-0.0021	-3.09	-0.0021	-3.1
OSi,t	0.0029	1.09	0.0031	1.17
ILS i,t	-0.4245	-1.32	-0.4197	-1.31
Size i,t	0.0000	0.05	0.0000	0.04
StockIMB i,t	0.0025	1.03	0.0025	1.03
$R_{i,t}$	-0.005	-0.93	-0.005	-0.97
$R_{i,t-1}$	-0.001	-0.1	-0.001	-0.11
$R_{i,t-2}$	0.002	0.32	0.002	0.38
$R_{i,t-3}$	0.004	0.89	0.004	0.88
$\sigma(Ret_i)$	0.003	0.15	0.004	0.2
Adj. R^2	0.067		0.067	
Avg. # stocks	586		586	

Table 7: Disagreements, Market Returns, Market Variance, and Aggregate News. Weekly Frequency

Panel A. Aggregate Equity News Index

Panel A.1	S&P500 Ret_t	t-stat	ΔVIX_t	t-stat
S&P500 Ret_{t-1}	-0.0470	-0.47	0.0180	0.57
ΔVIX_{t-1}	0.1241	0.44	-0.1035	-1.00
$News_{t-1}$	0.0004	0.51	0.0000	0.18
DIS-$Client_{t-1}$	-0.0424	-1.70	0.0180	2.45
DIS-$Inter._{t-1}$	-0.0843	-2.17	0.0158	1.42

Panel A.2	$News_t$	t-stat	DIS-$Client_t$	t-stat
S&P500 Ret_{t-1}	2.3496	0.63	0.0833	1.77
ΔVIX_{t-1}	19.7159	1.78	-0.0147	-0.08
$News_{t-1}$	0.1823	3.27	0.0003	0.65
DIS-$Client_{t-1}$	5.8098	3.62	0.9253	72.59
DIS-$Inter._{t-1}$	-0.8151	-0.37	-0.0872	-4.00

Panel A.3	DIS-$Inter._t$	t-stat
S&P500 Ret_{t-1}	0.0414	1.07
ΔVIX_{t-1}	0.1513	1.10
$News_{t-1}$	0.0006	1.56
DIS-$Client_{t-1}$	-0.0559	-4.80
DIS-$Inter._{t-1}$	0.8478	40.72

Panel B. US Macro News Index

Panel B.1	S&P500 Ret_t	t-stat	ΔVIX_t	t-stat
S&P500 Ret_{t-1}	-0.0373	-0.38	0.0180	0.57
ΔVIX_{t-1}	0.1525	0.56	-0.1036	-1.00
$News_{t-1}$	0.0003	1.30	0.0000	-0.24
DIS-$Client_{t-1}$	-0.0253	-0.89	0.0174	2.26
DIS-$Inter._{t-1}$	-0.0849	-2.18	0.0159	1.42

Panel B.2	$News_t$	t-stat	DIS-$Client_t$	t-stat
S&P500 Ret_{t-1}	26.6288	1.94	0.0847	1.81
ΔVIX_{t-1}	89.9944	2.07	-0.0116	-0.06
$News_{t-1}$	0.0875	1.80	-0.0001	-0.66
DIS-$Client_{t-1}$	-45.4704	-6.92	0.9237	65.00
DIS-$Inter._{t-1}$	2.5239	0.28	-0.0869	-4.00

Panel B.3	DIS-$Inter._t$	t-stat
S&P500 Ret_{t-1}	0.0416	1.05
ΔVIX_{t-1}	0.1492	1.05
$News_{t-1}$	-0.0003	-2.57
DIS-$Client_{t-1}$	-0.0666	-5.10
DIS-$Inter._{t-1}$	0.8488	41.11

Note to Table: We present the results of the VAR analysis. We estimate the model by maximum-likelihood. The t-statistics correspond to Newey-West t-statistics adjusted for 3 auto-correlation lags and are reported beside the parameter estimates. For estimation purposes, aggregate News Index, DIS-Client, and DIS-Intermediary are demeaned. In Panel A, aggregate news are proxied by aggregate equity news index. In Panel B, we use US macro news index to capture market-wide news. The sample period is from January 2005 to December 2013. The frequency is weekly.

Table 8: Disagreement and Investor Sentiment Indices

Panel A. Disagreements and Michigan Consumer Sentiment Inc Monthly Frequency

Panel A.1	$Sent_t$	t-stat	DIS-Client$_t$	t-stat
$Sent_{t-1}$	0.324	2.199	0.000	1.787
DIS-Client$_{t-1}$	52.672	1.904	0.894	26.504
DIS-Inter.$_{t-1}$	-157.799	-4.159	-0.066	-1.251

Panel A.2	DIS-Inter.$_t$	t-stat
$Sent_{t-1}$	0.000	2.082
DIS-Client$_{t-1}$	-0.017	-0.759
DIS-Inter.$_{t-1}$	0.977	23.401

Panel B. Disagreements and Baker and Wurgler (2006)'s Investor Sentiment Index. Monthly Frequency

Panel B.1	$Sent_t$	t-stat	DIS-Client$_t$	t-stat
$Sent_{t-1}$	0.653	6.803	0.008	1.023
DIS-Client$_{t-1}$	1.394	3.396	0.873	18.944
DIS-Inter.$_{t-1}$	0.420	0.938	-0.169	-2.518

Panel B.2	DIS-Inter.$_t$	t-stat
$Sent_{t-1}$	0.008	1.603
DIS-Client$_{t-1}$	-0.026	-1.067
DIS-Inter.$_{t-1}$	0.878	25.617

Note to Table: We present the results of the VAR analysis. We estimate the model by maximum-likelihood. The t-statistics correspond to Newey-West t-statistics adjusted for 3 auto-correlation lags and are reported beside the parameter estimates. For estimation purposes, DIS-Client, and DIS-Intermediary are demeaned. In Panel A, we report on the results obtained when Michigan sentiment index is used in the VAR model. In Panel B, we report on the results when when Baker and Wurgler (2006)'s sentiment index is used instead. The sample period is from February 2005 to December 2013. The frequency is monthly.

Appendix

A1: Descriptive statistics for Ravenpack Event Sentiment Score (ESS) reported in Equity Files
This table reports the average, standard deviation, and median ESS value,
as well as the number of observations per subject group.

	ESS			
RP Subject Group	**Avg**	**Std**	**Med**	**N**
'earnings'	54.26	15.36	50.00	359,277
'products-services'	65.49	7.15	64.00	168,013
'revenues'	54.22	12.18	50.00	138,056
'labor-issues'	52.15	4.92	54.00	103,371
'investor-relations'	50.04	0.20	50.00	98,348
'marketing'	52.16	3.27	50.00	93,273
'analyst-ratings'	56.82	20.13	51.00	89,442
'acquisitions-mergers'	55.98	12.16	49.00	53,312
'dividends'	53.07	9.66	50.00	46,967
'equity-actions'	53.69	12.94	50.00	41,493
'credit-ratings'	49.12	14.31	50.00	39,652
'partnerships'	60.86	2.25	61.00	30,161
'assets'	60.23	8.37	65.00	22,510
'credit'	54.16	10.24	52.00	17,890
'legal'	35.10	16.88	22.00	16,676
'regulatory'	32.35	14.30	22.00	3,501
'price-targets'	57.30	32.38	74.00	1,592
'corporate-responsibili	54.16	0.67	54.00	1,107
'indexes'	61.97	20.03	76.00	506
'exploration'	74.69	12.17	68.00	403
'industrial-accidents'	32.16	9.78	31.00	304
'bankruptcy'	14.13	16.26	7.00	123
'government'	50.00	0.00	50.00	92
'security'	34.35	18.91	26.00	86
'war-conflict'	44.44	23.26	44.00	50
'balance-of-payments'	72.53	31.64	91.00	45
'civil-unrest'	45.06	8.71	44.00	36
'insider-trading'	33.00	0.00	33.00	24
'transportation'	36.00	0.00	36.00	23
'crime'	31.27	2.81	32.00	15
'public-opinion'	50.00	0.00	50.00	2
'taxes'	75.00	0.00	75.00	2

A2: Descriptive statistics for Ravenpack Event Sentiment Score (ESS) reported in the Global Macro Files

This table reports the average, standard deviation, and median ESS value,
as well as the number of observations per subject group.

	ESS			
RP Subject Group	**Avg**	**Std**	**Med**	**N**
'balance-of-payments'	48.46	29.12	50	5651
'consumption'	48.68	24.76	50	4642
'foreign-exchange'	42.62	32.14	17	4581
'employment'	55.28	29.71	50	4032
'credit'	53.59	6.47	55	4010
'domestic-product'	60.37	34.74	50	3608
'production'	49.82	29.27	50	2007
'housing'	49.63	20.65	50	1222
'interest-rates'	45.87	23.08	50	925
'public-finance'	47.87	27.28	30	233
'taxes'	56.01	13.78	50	162
'business-activity'	41.00	33.30	17	11