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ABSTRACT

We test the hypothesis of Avramov, Chordia, and Goyal (2006) that asymmetric volatility is governed by the trading dynamics of informed and uninformed traders; uninformed trades increase volatility following asset price declines while informed trades decrease volatility following asset price increases. Using a dataset that directly distinguishes between informed and uninformed trades, we find that only the trading activity of small liquidity traders (i.e. retail investors) accounts for the asymmetric volatility relationship. Thus, the hypothesis of Avramov et al. is only partially supported.

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I. INTRODUCTION

Asymmetric volatility is a stylized fact referring to the negative relationship between current price return and future return volatility. Two hypotheses proposed to explain the phenomenon are the leverage effect (Black 1976; Christie 1982) and the volatility feedback (Pindyck 1984; French, Schwert, and Stambaugh 1987; Campbell and Hentschel 1992). A recent study by Avramov, Chordia, and Goyal (2006) (ACG, hereafter) proposes a new hypothesis that asymmetric volatility is governed by the trading dynamics of informed traders and liquidity traders. This paper aims to validate this proposition.

Although ACG's hypothesis is theoretically appealing, no direct empirical test of which we are aware has been conducted. ACG do not have direct measures for informed trades and uninformed trades. Instead, the authors assume that selling activity on trading days experiencing negative return shocks is dominated by uninformed (herding) traders who sell after price declines, and selling activity on trading days experiencing positive return shocks is dominated by informed (contrarian) traders who sell after price increases.

ACG's method of classification for informed and uninformed trades is ambiguous for several reasons. First, ACG assume that return shocks trigger trades. Prior literature documents a strong contemporaneous relationship between price returns and trading activity at the daily frequency (Chan and Fong 2000; Chordia, Roll, and Subrahmanyam 2002), but at the intraday level, Chordia, Roll, and Subrahmanyam (2005, 2008) show that trading activity leads stock returns by a few minutes. Thus, it is possible that trading activity causes return shocks, a causal direction that is contrary to ACG's assumption.

Second, selling activity on a given trading day is not necessarily dominated by one type of traders. Recent studies (e.g. Evans and Lyons 2008) argue that the mapping functions from news into asset prices can be complicated, and that price discovery is carried through trades among traders with heterogeneous opinions (Shalen 1993; Harris and Raviv 1993). Evans and Lyons (2008) show that a large portion of price adjustment in foreign exchange markets is processed through trading activities. Thus, asset prices can result from the trades of more than one group of traders.

Third, because of a strong positive contemporaneous relationship between trading activity and price returns, high selling activity is likely to be associated with large negative return shocks. The interaction of the two variables may emphasize the high magnitude of the negative return shocks. Consequently, if the asymmetric volatility relationship between current returns and future volatility is not linear, the interaction of the two variables could simply capture the nonlinearity in the relationship.

We test ACG's hypothesis on the Nasdaq-100 index futures contract. We employ the Computer Trade Reconstruction (CTR) dataset which contains a classification code that allows us to directly distinguish informed trades from liquidity trades. Similar to Daigler and Wiley (1999), we assign traders who have access to a trading floor (i.e. floor traders and floor brokers) as informed traders and traders who do not have access to a trading floor (i.e. the general public) as uninformed traders. Hence, our informed traders have superior information due to their ability to observe the sources of trades, short-term price deviations, and order imbalances at a given

time. We argue that this type of information is more consistent with the hypothesis of ACG that informed trades reduce volatility.¹

We separate our uninformed trades into large and small trades because recent empirical studies document differences in trading behavior and price impacts between large and small liquidity traders (Kumar and Lee 2006; Kaniel, Saar, and Titman 2008; Frino, Bjursell, Wang and Lepone 2008). Thus, we classify our transactions into informed trades, small liquidity trades, and large liquidity trades.²

We find that our preliminary results are similar to those reported in ACG. The coefficient representing the asymmetric volatility relationship is negative and statistically significant when not controlling for selling activity. However, after incorporating a selling activity measure, the coefficient becomes positive and the negative relationship is absorbed by the interaction between return shocks and selling activity. We then divide selling activity among our trader types and re-estimate the model. We find that only the selling activity of retail investors accounts for the asymmetric volatility relationship. The selling activities of large liquidity traders and informed traders do not significantly impact asymmetric volatility. Our results are robust to a number of robustness checks. Hence, we conclude that the hypothesis of ACG is only partially supported.

In considering potential economic explanations of how retail investors' trades can account for asymmetric volatility, we examine the levels of selling activity of retail investors associated with different levels of price-return shocks. We find that the selling activity associated

¹ The other type of information is private information regarding changes in future expected payoffs of the assets. Informed traders acting on this information may adopt profit-maximization trading strategies that may increase volatility and are inconsistent with the hypothesis.

² We also experiment dividing informed trades into large and small trades. Our conclusion is qualitatively the same.

with positive return shocks is slightly higher than average, but the selling activity associated with negative return shocks exhibits a quadratic pattern. It falls below average when the negative return shocks are small but becomes significantly above average when the negative return shocks are large. This pattern rules out the positive-feedback trading hypothesis of De Long, Shleifer, Summers, and Waldmann (1990) that uninformed traders sell (buy) when prices begin to decline (increase). Our results could be explained by a combination of the disposition effect hypothesis (Kahneman and Tversky 1979; Shefrin and Statman 1985; Odean 1998) and the liquidity-provider hypothesis of Kaniel, Saar, and Titman (2008). That is, retail investors perceive small return shocks as temporary and act as liquidity providers who trade contrarily with other traders, thus lowering market volatility. However, as negative return shocks become large, retail investors realize that the negative shocks are not temporary and rush to dispose of their position, intensifying market volatility. This trading behavior underlies the asymmetric volatility.

Daigler and Wiley (1999), Chen and Daigler (2008), and Frino et al. (2008) also use the CTR dataset but examine different research questions. The first two papers focus on the impacts of informational trades and non-informational trades on the positive volume-volatility relationship. Frino et al. analyze the contemporary and the permanent price impacts of large liquidity traders.

II. BACKGROUND

Asymmetric volatility has been extensively documented in stock returns. Two hypotheses are proposed to explain this phenomenon. First, the leverage effect hypothesis (Black 1976;

Christie 1982) proposes that negative return shocks increase a firm's leverage, making the firm's assets riskier and its price more volatile. Second, the time-varying expected return or volatility feedback hypothesis (Pindyck 1984; French, Schwert, and Stambaugh 1987; and Campbell and Hentschel 1992) argues that investors anticipate increases in future volatility and require a higher rate of return as compensate for the anticipated risk increase. The current asset price must drop in order to produce higher expected returns, resulting in negative current returns. The two hypotheses lead to opposite causal conclusions. The leverage effect suggests that current negative-return shocks lead to higher future volatility while the volatility feedback effect suggests that anticipated higher future volatility leads to current negative returns.

In empirical tests, Bekaert and Wu (2000) report that asymmetric volatility is primarily driven by the volatility feedback effect at the firm level, and that the leverage effect explains only a small portion of this phenomenon. Wu (2001) incorporates both effects into his model and finds that the leverage effect contributes more than twice as much to asymmetric volatility than the volatility feedback effect does. However, the magnitude of the volatility feedback effect can be very large during high volatility periods.

ACG (2006) argue that the two hypotheses above are unlikely to explain asymmetric volatility in high-frequency data because an investor's risk attitude will not frequently change. This is despite the fact that prior empirical studies find asymmetric volatility at the daily frequency. ACG propose a trading-based explanation wherein the dynamic interplay between informed and non-informed (liquidity-driven) trades is responsible for higher-frequency asymmetric volatility. ACG show that selling activity associated with positive return shocks

(assumed to be dominated by informed trades) leads to a reduction in future volatility and selling activity associated with negative return shocks (assumed to be dominated by non-informed, herding trades) leads to an increase in future volatility.

III. DATA AND MEASURES

A. The CTR Dataset

We employ the Computer Trade Reconstruction (CTR) dataset to examine the impact of trading activity by different trader types on asymmetric volatility. Our sample comprises transactions on Nasdaq-100 index futures contracts between 2002 through 2004 (756 trading days). The CTR dataset is the major audit trail source used by the Commodity Futures Trading Commission (CFTC) to track every transaction in the market. The data are constructed from trading cards submitted by traders to the exchange clearinghouse for settlement and reconciliation purposes at the end of each trading day. The CTR dataset contains the following information: commodity code, trading date, time, price, quantity, trade direction (i.e., buy or sell), identification of executing traders, and classification of executing traders.

We use trading volume as a trigger to rollover the futures contracts and use only transactions that occur during the trading hours (from 8:30-15:15 CT). We drop observations whose transaction-by-transaction returns are greater than 1 percent (a total of 47 observations or about 0.002% of the sample). Many of these extreme price changes are associated with large quantity trades. As a robustness check, we find that our results are qualitatively unchanged if all the data are used.

We analyze daily price returns calculated from the last transaction price before market is closed. Following ACG, the selling measure is defined as the number of sell trades divided by the total number of trades. We aggregate all trades within a trading day using all observations and adjust for double recording. The average (median) number of trades per day is 3,005 (2,890).

B. Classification of Traders

According to CFTC, the trader classification (known as the Customer Type Indicator, CTI) consists of four trader types. The CTI1 classification refers to a local floor trader who trades from their own account. Most of these traders are market makers or scalpers. A CTI2 trader is a clearing member who trades from the clearing member's house account. Clearing members usually trade to benefit from mispricing or for long-term hedge and arbitrage purposes. A CTI3 trader is another floor trader who trades for accounts of other members, including brokers. The CTI4 classification refers to the general public or any other trader who is not on the trading floor (e.g. retail traders, managed futures funds). CTI classification is used industry-wide and traders are strictly assigned based on the definitions above.

According to Daigler and Wiley (1999), CTI1s are market makers who trade in response to the demand of other traders. CTI2s and CTI3s are floor traders who trade for speculative and hedging purposes. These traders have up-to-the-minute information about the supply and demand dynamics of futures and cash markets. CTI2s and CTI3s can directly observe the source of trades, the short-term direction of price, and the order imbalance in the markets. Based on these characteristics, we designate CTI2s and CTI3s as informed traders and CTI4s as uninformed traders.

Note that our informed traders have superior information in terms of trading dynamics, short-term direction of prices, and order imbalance as opposed to private information about changes in expected future payoffs. According to the inventory theory (Chordia and Subrahmanyam 2004), informed traders acting on this information help market makers rebalance their inventories and bring asset prices back to their fundamentals. This type of informed trades is consistent with ACG's hypothesis that informed trades reduce future volatility.

We do not assume that our informed traders are privately informed about changes in expected future payoffs of the asset. In fact, our sample asset is an index future where private information is unlikely to occur due to diversification (Subrahmanyam 1991). In addition, informed traders acting on private information may adopt some profit-maximization trading strategies that may aggravate price volatility, contrary to ACG's hypothesis. Thus, the informational characteristics of CTI2 and CTI3 traders are suitable for testing ACG's hypothesis.

Because a CTI1 trader is a market-maker who accommodates the orders of other traders, an order is designated as seller-initiated (buyer-initiated) trade if a trader sells to (buys from) a CTI1 trader.³ We exclude transactions that do not trade with CTI1 traders and transactions that trade between CTI1 traders because we are unable to identify the trade initiators.

Table 1 summarizes trading activity by each trading pair where buyers are in columns and sellers are in rows. Trading activity is measured by the number of transactions and number of contracts. For example, over the sample period CTI4 traders buy 23.77% (28.85%) of total transactions (contracts) from CTI1s. Most transactions (about 85% of total contracts and 91% of

³ Manaster and Mann (1996) discuss that CTI1 traders aggressively manage their inventory. According to the inventory theory, CTI1 traders manage their inventory by setting prices to attract trades.

total transactions) are conducted with CTI1 traders, supporting the market-making role of CTI1s. The second most active traders are off-floor traders, classified as CTI4, whose trades account for 55% (73%) of total transactions (contracts). About 42% of total transactions are trades of only one contract, and about 70% percent involve trades of 4 contracts or less.

Recent literature suggests that large trades may have a different impact from that of small trades. ACG find that, for contrarian trades, selling activity measured in the number of shares significantly influences the degree of asymmetric volatility while selling activity measured in the number of transactions does not. Kumar and Lee (2006) and Kaniel et al. (2008) find that retail investors are liquidity suppliers who trade as contrarians. Frino et al. (2008) find that, in futures markets, large liquidity orders carry different information sets than do small liquidity orders. Consequently, we separate large liquidity trades from small liquidity trades. Following Frino et al., we define transactions that trade more than k contracts as large liquidity trades, where k is set equal to 1, 4, 9, or 12 which correspond to the 50th, 75th, 90th, and 95th percentiles, respectively. As such, traders are classified as small liquidity traders (SL), large liquidity traders (LL), or informed traders (IN).

C. Volatility Measure

To gain efficiency, we compute the realized volatility measure suggested by Bandi and Russell (2006). Andersen and Bollerslev (1998) and Andersen, Bollerslev, Diebold, and Labys (2003) argue that realized volatility calculated from intraday returns is an unbiased and highly efficient estimator of return volatility. In addition, the distribution logged realized volatility is approximately Gaussian (Bollerslev, Diebold, and Labys 2001). However, realized volatility

computed from discrete-time observable prices is contaminated by market microstructure imperfections (Bandi and Russell 2006; Barndorff-Nielsen and Shephard 2002, 2004; Hansen and Lunde 2005; Ait-Sahalia, Mikland, and Zhang 2005). Bandi and Russell propose a method to choose the optimal sampling frequency to minimize microstructure effects and to maximize estimate efficiency. We calculate the realized volatility based on the Bandi and Russell method. A detailed calculation is given in Appendix A.

VI. Methodology and Empirical Results

A. Preliminary Statistics

Table 2 reports descriptive statistics in the upper panel. During 2002 through 2004, the mean (median) daily return is approximately zero (0.12) with minimum of -6.4 percent and maximum of 10.3 percent. The autocorrelation coefficients of the return series are close to zero and the Chi-square test for the first six lagged returns is not statistically significant. The average (median) realized volatility of returns is 1.65 (1.50) percent with standard deviation of 0.4 percent and it is highly autocorrelated. We find that the log of the realized volatility is approximately normal, consistent with Andersen et al. (2001).

<< Place Table 2 here >>

On average, the proportion of sell trades (to total trades) by all traders is 0.5 when measured by the number of transactions and 0.25 when measured by the number of contracts. This finding suggests that most selling transactions are from trades of a small number of contracts. If we define transactions of more than 9 contracts as large orders, the average selling

activity for informed traders, large liquidity traders, and small liquidity traders are respectively 0.03, 0.04, and 0.18 (0.03, 0.13, and 0.09) when measured by the number of transactions (contracts). All selling activity measures are positively autocorrelated.

The lower panel of Table 2 reports the correlation coefficients. We observe a small contemporaneous correlation between returns and return volatility. The selling activity by informed (large liquidity) traders is positively (negative) correlated with volatility. The correlation between selling activities by large liquidity traders and informed traders is negative and highly statistically significant, suggesting that the two traders trade counter to each other. We also find that small liquidity traders are likely to trade counter to large liquidity traders given that the correlation between them is significantly negative.

B. Test for Informed versus Uninformed Trades

So far, we follow the methodology of Daigler and Wiley (1999) in determining who are informed and liquidity traders. To formally investigate the behavior of informed trades versus uninformed trades, we examine Campbell, Grossman, and Wang (1993)'s hypothesis that liquidity trades generate negatively autocorrelated returns while informational trades do not generate autocorrelated returns.

Recent literature in individual stocks shows that informed trades can produce positive autocorrelated returns as informed traders split their orders and submit them over a period of time. However, we expect that our informed trades would not generate significant autocorrelation given that Llorente, Michaely, Saar, and Wang (2002) suggest that the degree of autocorrelation depends on the degree of private information. Because our sample is a basket of

broad assets (index futures), private information is less likely to be contained in their trades than would be for trades of individual stocks due to diversification (Subrahmanyam 1991).

Similar to Campbell et al. (1993), we specify our model as:

$$r_t = \alpha_0 + \left(\sum_{i=1}^5 \alpha_i D_{i,t} + \beta_{SL} \frac{NS_{t-1}^{SL}}{NT_{t-1}} + \beta_{LL} \frac{NS_{t-1}^{LL}}{NT_{t-1}} + \beta_{IN} \frac{NS_{t-1}^{IN}}{NT_{t-1}} \right) r_{t-1} + \delta_1 \frac{NS_t}{NT_t}, \quad (1)$$

where r_t is price returns at time t , $D_{i,t}$ is a day-of-the-week dummy variable, NT_t is the total number of trades, and NS^{SL} , NS^{LL} , and NS^{IN} are respectively numbers of sell trades by small liquidity traders, large liquidity traders, and informed traders. NS_t is the sum of NS^{SL} , NS^{LL} , and NS^{IN} . Following Campbell et al., we allow first order autocorrelation to vary with the day-of-the-week effect which, subsequently, we find a better fit in terms of R^2 . We include a contemporaneous selling activity variable because Chan and Fong (2000), Chordia, Roll, and Subrahmanyam (2002), and others document a strong correlation between returns and order imbalance.

<< Place Table 3 here >>

The results of our tests are presented in Table 3. The t-statistics are estimated using OLS with Newey and West (1987) heteroscedasticity-robust standard errors. Our hypotheses are that liquidity trades exhibit negative return autocorrelation ($\beta_{SL} < 0$ and $\beta_{LL} < 0$) and that informed trades result in no autocorrelation ($\beta_{IN} = 0$).

Our results indicate that large liquidity trades generate negative autocorrelation while informed trades and small liquidity trades do not. The β_{LL} coefficient is negative and statistically significant across different cutoffs and measures of selling activity. The magnitude of the

coefficient becomes larger as the cutoff level increases again indicating that large liquidity trades result in larger negative autocorrelation. The β_{SL} and β_{IN} coefficients are positive when selling activity is measured by number of contracts and are negative when selling activity is measured by number of transactions. However, the two coefficients are not statistically significant different from zero. These results validate our classification of large liquidity and informed trades.

The classification for small liquidity trades may not be validated by the model, but it is consistent with recent studies. Kaniel et al. (2008) argue that retail investors are liquidity providers to institutional investors who demand immediacy. Frino et al. (2008) show that large liquidity trades have larger temporary price effects than small liquidity trades. Hence, the negative autocorrelation in the model is more likely to be associated with large liquidity trades than with small liquidity trades. Taken together, our results suggest that large orders of CTI4 traders are liquidity trades and orders of floor traders (CTI2 and CTI3) are informed.

C. ACG's Asymmetric Volatility Tests

We now investigate whether ACG's hypothesis applies to our stock-index futures sample. We implement ACG's methodology with the exception that we replace the absolute return shock by the log of realized volatility. To do this, we first estimate the unexpected returns from the following equation:

$$r_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \zeta_0 \frac{NS_t}{NT_t} + \sum_{i=1}^{10} \lambda_i r_{t-i} + \varepsilon_t \quad (2.0)$$

where r_t is daily price return at time t , $D_{i,t}$ are day-of-the-week dummy variables, NT is a number of trades, and NS is a number of sells. We include 10 lagged dependent variables to account for

autocorrelation. Similar to ACG, we then perform the tests in three steps with the following specifications:⁴

$$y_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \phi_0 \varepsilon_{t-1} + e_t \quad (2.1)$$

$$y_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \left(\phi_0 + \phi_1 \frac{NS_{t-1}}{NT_{t-1}} \right) \varepsilon_{t-1} + e_t \quad (2.2)$$

$$y_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \left(\phi_0 + \phi_1^+ \frac{NS_{t-1}}{NT_{t-1}} (\varepsilon_{t-1} \geq 0) + \phi_1^- \frac{NS_{t-1}}{NT_{t-1}} (\varepsilon_{t-1} < 0) \right) \varepsilon_{t-1} + e_t, \quad (2.3)$$

where y_t is the log of realized volatility, $(\varepsilon_{t-1} \geq 0)$ is an indicator variable equal to 1 if ε_{t-1} is greater than or equal to zero and, similarly, $(\varepsilon_{t-1} < 0)$ is equal to 1 if ε_{t-1} is less than zero. The selling activity is defined as the number of sells divided by the number of total transactions (NS/NT). The models are again estimated by OLS employing the Newey-West (1987) heteroscedasticity-robust variance-covariance matrix.

<< Place Table 4 here >>

Our results are reported in Table 4 and are similar to those reported in ACG. Specifically, when the selling variable is not included in the model specification as in Eq. (2.1), the coefficient of the lagged return shock (ϕ_0) is negative and statistically significant. This finding suggests asymmetric volatility in the price returns. Considering Eq. (2.2) where the aggregate selling activity is included, we find that the ϕ_0 coefficient becomes positive and

⁴ Earlier literature (e.g. Bessembinder and Sequin 1992, 1993; Wang and Yau 2000) find futures returns volatility is a function of Open Interests. In our unreported results, we find that when the total trade variable, NT, is included in the model specification, the coefficient of the Open Interest becomes insignificant suggesting that at least NT carries the same information as Open Interest.

remains statistically significant. The ϕ_1 coefficient of the lagged return shock conditional on aggregate selling activity is negative and statistically significant, suggesting that the asymmetric volatility found in specification (2.1) appears only in conjunction with the selling activity. Finally, when we condition the selling activity on positively-lagged return shocks and negatively-lagged return shocks, respectively, we find that both the ϕ_1^+ and the ϕ_1^- coefficients are negative.

The coefficients in our models are more statistically significant when the selling activities are measured by number of contracts. We observe a slight increase in R^2 when conditioning selling activities on the signs of the lagged return shocks. Overall, our results resemble those of ACG and we conclude that ACG's hypothesis applies to our index-futures sample.

D. Asymmetric Volatility Tests with Trader Classification

ACG hypothesize that asymmetric volatility is the result of selling pressure being dominated by noise traders on negative-return days and by informed traders on positive-return days. We directly test this hypothesis by altering Eq. (2.2) by dividing the selling activity measure by trader type. Our resulting specification is as follows:

$$y_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \left(\phi_0 + \phi_{SL} \frac{NS_{t-1}^{SL}}{NT_{t-1}} + \phi_{LL} \frac{NS_{t-1}^{LL}}{NT_{t-1}} + \phi_{IN} \frac{NS_{t-1}^{IN}}{NT_{t-1}} \right) \varepsilon_{t-1} + e_t \quad (2.4)$$

where NS^{SL} , NS^{LL} and NS^{IN} are numbers of sells by small liquidity traders, large liquidity traders, and informed traders, respectively. Note that the sum of the three selling activity variables is the NS in Eq. (2.2), which is previously shown to govern the asymmetric volatility relation.

<< Place Table 5 here >>

Table 5 reports the regression results using different cutoffs for the separation of large and small liquidity trades. Our results indicate that the source of asymmetric volatility is selling activity of small liquidity traders. The selling activity of large liquidity and informed trades does not impact the asymmetric volatility relationship. Similar to ACG, the results are stronger when selling activity is measured by the number of contracts, suggesting that quantity of trades is more important than frequency of trades.

When the selling activity is measured by the number of contracts, the ϕ_{SL} coefficient is negative and statistically significant at the 1-percent level. The ϕ_{LL} coefficient is negative and statistically significant only when using 2 and 4 contracts as cutoffs (in column k=2 and k=4) and becomes insignificant when using 9 contracts or more as the cutoff. These results suggest that asymmetric volatility is governed by small to medium-sized liquidity transactions. The ϕ_{IN} coefficient is negative but it is not statistically significant in any estimate. These results suggest that only liquidity traders' selling activity accounts for asymmetric volatility.

We further investigate whether there is a relationship between statistically significant liquidity trader selling and the significance of the selling activity (which is conditioned on the sign of the return shocks) in Eq. (2.3). To do this, we modify Eq. (2.3) by dividing the selling activity measure by trader type as follows.

$$\begin{aligned}
 y_t = & \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \phi_0 \varepsilon_{t-1} + \left(\phi_{SL}^+ \frac{NS_{t-1}^{SL}}{NT_{t-1}} + \phi_{LL}^+ \frac{NS_{t-1}^{LL}}{NT_{t-1}} + \phi_{IN}^+ \frac{NS_{t-1}^{LL}}{NT_{t-1}} \right) (\varepsilon_{t-1} \geq 0) \varepsilon_{t-1} \\
 & + \left(\phi_{SL}^- \frac{NS_{t-1}^{SL}}{NT_{t-1}} + \phi_{LL}^- \frac{NS_{t-1}^{LL}}{NT_{t-1}} + \phi_{IN}^- \frac{NS_{t-1}^{LL}}{NT_{t-1}} \right) (\varepsilon_{t-1} < 0) \varepsilon_{t-1} + e_t
 \end{aligned} \tag{2.5}$$

<< Place Table 6 here >>

Consistent with our earlier results, the ϕ_{SL}^+ and ϕ_{SL}^- coefficients are negative and statistically significant. Results are available on request. The coefficients of the selling activity of large liquidity traders and informed traders are generally not statistically significant. The ϕ_{IN}^+ coefficient of the selling activity of informed traders conditional on positive return shocks is positive (but not statistically significant), contradicting ACG's hypothesis that informed trades reduces the degree of asymmetric volatility. None of the tests on the difference between ϕ_{SL}^+ and ϕ_{SL}^- coefficients can reject the hypothesis that the two coefficients are different. Overall, these results confirm that the significant coefficients of the selling activity, conditional on the signs of the returns shocks, are driven by the significant coefficient of the selling activity by small liquidity traders. Hence, only the selling activity of small liquidity traders accounts for the asymmetric volatility relationship.

V. POTENTIAL ECONOMIC EXPLANATIONS

We consider some possible explanations of how the trades of small liquidity traders (i.e. retail investors) can cause asymmetric volatility. Our results and those of ACG (2006) suggest that the selling activity associated with positive-return shocks reduces volatility while the selling activity associated with negative-return shocks increases volatility. For an explanation to be plausible, it should account for changes in volatility following both positive return shocks and negative return shocks.

To examine the association between return shocks and the level of selling activity, we calculate average selling activity (i.e. number of sells divided by number of trades) at different levels of return shocks. We first divide our return shocks into positive and negative shocks. Next, we further divide the positive (negative) return shocks into four bins according to size and label the bins 1 to 4 (-1 to -4) where bin 4 (-4) contains largest positive (negative) return shocks. Using observations (about 94 observations) in each bin, we calculate the average selling activity for each bin less the full-sample average.

Figure 1 plots the average selling activity of retail investors on the y-axis against size-sorted return shocks on the x-axis. An average selling activity that is greater (less) than zero suggests that retail investors sell more (less) than average. The figure suggests that retail investors' selling activity reacts asymmetrically with return shocks.⁵ The selling activity associated with positive return shocks (bins 1 to 4) is slightly positive but is not statistically significant. However, for negative return shocks, selling activity is significantly above average for the largest negative-return shocks (bin -4) and declines significantly to below average for small- and medium-sized negative return shocks (bins -3 to -1). This pattern suggests that retail investors are less likely to sell when negative return shocks are small, but become intense sellers when negative return shocks are large.

<< Place Figure 1 here >>

⁵ For selling activity of large liquidity traders and informed traders, the figures (not reported) are symmetrical and mirror each other.

A. The Positive Feedback Trading Hypothesis

De Long, Shleifer, Summers, and Waldmann (1990) suggest that noise traders can move an asset's price farther away from its fundamental value by adopting a trend-chasing strategy (i.e. buy when prices begin to rise and sell when prices begin to fall). Antoniou, Homles, and Priestley (1998) argue that the reaction of positive-feedback traders to bad news is greater than it is to good news, resulting in asymmetric volatility. For this hypothesis to explain our results, small liquidity traders must sell when prices begin to fall thus aggravating price volatility. However, we observe that the relationship between retail investor's selling activity and small, negative-return shocks is below average. Our results are contrary to the trend-chasing strategy and are not explained this hypothesis.

B. The Disposition Effect Hypothesis

The disposition effect is the tendency for investors to hold losing investments too long and sell winning investments too soon (Kahneman and Tversky 1979; Shefrin and Statman 1985; Odean 1998). The tendency to sell winning investments too soon reduces volatility when asset prices increase while the tendency to hold losing investments too long intensifies volatility when price declines are large. This hypothesis is consistent with the selling pattern of retail investors observed in Figure 1. That is, retail investors' selling activity is slightly above average when prices begin to rise but is below average when prices begin to fall. Only when negative-return shocks are large does retail investors' selling activity significantly increase. A minor puzzle from this result would be why selling activity drops significantly below average when prices begin to fall. We introduce a third hypothesis to help explain this puzzle.

C. The Liquidity Provider Hypothesis

Recent studies (Choe, Kho, and Stulz 1999; Grinblatt, Keloharju 2000, 2001; Kaniel et al. 2008) document the contrarian trade behavior of retail investors.⁶ Theories by Stoll (1978), Grossman and Miller (1988), Campbell et al. (1993), and Chordia and Subrahmanyam (2004) suggest that investors who require immediacy (i.e. large institutional investors) offer price concessions to induce risk-averse investors to take the other side of the transactions. Kaniel et al. (2008) hypothesize that retail investors act as liquidity providers to institutional investors who require immediacy by selling stocks that outperform markets and by buying stocks that underperform markets. Figure 1 shows that the selling activity of retail investors is above (below) average when prices begin to rise (fall), which is consistent with this argument. However, if retail investors are contrarian traders, the selling activity would reduce volatility, meaning that this hypothesis alone is not adequate to explain our results.

We conjecture that our results can be explained by a combination of the disposition effect and the liquidity-provider effect. For small price changes, retail investors view the price change as temporary and adopt a contrarian trading strategy in expectation of short-term profits where they sell (buy) when prices begin to increase (fall). This has the effect of lowering market volatility. However, for large negative-return shocks, retail investor realize that the price drop may not be temporary and rush to dispose of their position thus aggravating market volatility. The combination of these two effects explains the asymmetric volatility relationship where

⁶ Grinblatt and Keloharju (2001) find household investors are momentum traders in response to recent returns but contrarian traders in response to longer past returns.

contrarian trading behavior dominates when return shocks are positive and the disposition effect dominates when the returns shocks are largely negative.

The last remaining puzzle is that retail investors rush to dispose of their positions only when return shocks are largely negative. Given that our sample asset is an index future, retail investors can take either long or short position and, thus, may suffer losses from either positive or negative return shocks. For our hypotheses to hold, retail investors must suffer from cognitive bias that causes them to prefer an investment that takes a long position on the assets. This conjecture is consistent with Figure 1 where we find that retail investors' selling activity reacts asymmetrically only to negative-return shocks. We leave a formal test of this conjecture for future research.

VI. SUMMARY AND CONCLUSION

We investigate the Avramov, Chordia, and Goyal (2006) proposition that asymmetric volatility is governed by the trading dynamics between informed and uninformed traders. Using the Computer Trade Reconstruction (CTR) dataset that directly classifies different traders, we find our results in the Nasdaq-100 index futures similar to those of ACG in individual stocks. However, after dividing our selling activity measure by trader type (i.e. small liquidity traders, large liquidity traders, and informed traders), we find that only the selling activity of small liquidity investors accounts for. The selling activities of large liquidity traders and informed traders do not significantly impact asymmetric volatility. Hence, the hypothesis of ACG is only partially supported. We infer that asymmetric volatility caused by retail investors' trading

behavior can be explained by a combination of the disposition effect and liquidity-provider hypotheses.

APPENDIX A: CALCULATION OF REALIZED VARIANCE

Bandi and Russell (2006) and Ait-Sahalia, Mykland, and Zhang (2005) propose estimating the efficient realized variance from optimal sampling frequency that minimizes the mean square error (MSE) of the estimate. We adopt the Bandi and Russell method, and the results are virtually the same if the Ait-Sahalia et al. approach is used. The optimal sampling frequency is $\delta^* = 1/M^*$ where M^* solves the following condition.

$$\{M^* = M : 2M^3 A + M^2 B - 2Q = 0\}$$

where r_i is the intraday period return, $A = \left(\frac{\sum_{i=1}^{m_1} r_i^2}{m_1} \right)^2$, $B = 2 \frac{\sum_{i=1}^{m_1} r_i^4}{m_1} - 3A$, and $Q = \frac{m_2}{3} \sum_{i=1}^{m_2} r_i^4$

M^* is allowed to be time-varying and, thus, differ across trading days. Bandi and Russell suggest using the highest frequency possible for m_1 in A and B and a 15-minute frequency to calculate Q ($m_2= 27$). M^* is restricted to a positive number only. For our sample, the optimal M^* ranges from 15.9 to 503.5 with a mean (median) of 141.1 (135.6). The realized volatility is the square root of the realized variance estimated as follows:

$$RV_t = \sum_{i=1}^{m_t^*} r_{t,i}^2,$$

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Table 1 Percentage trading activity by trader pairs.

Buyers are on rows and sellers are on columns. Transactions that cannot identify traders on the opposite position are coded as “N/A.”

Traders	CTI1	CTI2	CTI3	CTI4	N/A	Total
Panel A: By number of transactions (N)						
CTI1	37.44	1.43	1.68	22.56	0.12	63.23
CTI2	1.57	0.09	0.08	0.72	0.01	2.46
CTI3	2.04	0.08	0.07	1.32	0.00	3.51
CTI4	23.77	0.69	1.23	5.00	0.11	30.79
Sum	64.82	2.29	3.05	29.59	0.25	100.00
Panel B: By number of contracts (Q)						
CTI1	18.02	2.19	1.25	28.82	0.12	50.41
CTI2	2.41	0.23	0.16	1.68	0.01	4.48
CTI3	1.54	0.16	0.13	1.94	0.00	3.78
CTI4	28.85	1.53	1.79	9.03	0.14	41.34
Sum	50.82	4.11	3.33	41.47	0.27	100.00

Table 2 Summary statistics.

Returns are daily returns using close-to-close prices. RV is Bandi and Russell (2006)'s realized volatility. Trading activities are measured in terms of number of transactions and number of contracts. NT is the total number of trades. NS^{SL} , NS^{LL} , and NS^{IN} are the number of sales by small liquidity traders, large liquidity traders, and informed traders. NS is the sum of NS^{SL} , NS^{LL} , and NS^{IN} . Liquidity-based transactions with more than 9 contracts are considered as large orders. ρ_1 and ρ_6 are the first- and sixth-order autocorrelation. The Chi-square statistic tests the statistical significance of the first six order autocorrelation.

Variables	N	Mean	St. Dev	Median	Min	Max	ρ_1	ρ_6	χ^2	p-value
Return	756	0.00	1.88	0.12	-6.41	10.28	-0.03	-0.02	5.08	0.53
RV	756	1.65	0.68	1.50	0.41	4.65	0.86	0.79	3089.21	0.00
<u>Transactions</u>										
NT	756	1612	531	1540	256	3734	0.75	0.66	2256.55	0.00
NS/NT	756	0.50	0.03	0.50	0.37	0.65	0.19	0.04	59.18	0.00
NS^{SL}/NT	756	0.18	0.02	0.18	0.12	0.28	0.27	0.13	186.76	0.00
NS^{LL}/NT	756	0.04	0.01	0.04	0.01	0.09	0.45	0.37	711.64	0.00
NS^{IN}/NT	756	0.03	0.01	0.03	0.01	0.06	0.60	0.51	1396.20	0.00
<u>Contracts</u>										
NT	756	16350	4911	16159	2362	39190	0.44	0.30	632.02	0.00
NS/NT	756	0.25	0.03	0.25	0.13	0.35	0.11	0.02	22.37	0.00
NS^{SL}/NT	756	0.09	0.02	0.09	0.05	0.19	0.51	0.41	984.70	0.00
NS^{LL}/NT	756	0.13	0.04	0.13	0.05	0.25	0.39	0.34	601.25	0.00
NS^{IN}/NT	756	0.03	0.01	0.02	0.00	0.08	0.61	0.55	1556.51	0.00
<u>Correlations</u>										
	Log(RV)	Transactions				Contracts				
		NS/NT	NS^{SL}/NT	NS^{LL}/NT	NS^{IN}/NT	NS/NT	NS^{SL}/NT	NS^{LL}/NT	NS^{IN}/NT	
Return	-0.063	0.068	0.152	-0.218	0.125	-0.443	-0.141	-0.317	0.068	
Log(RV)		0.014	-0.064	-0.308	0.497	0.034	0.356	-0.382	0.620	
NS/NT										
NS^{SL}/NT		0.759				0.278				
NS^{LL}/NT		0.326	-0.115			0.705	-0.400			
NS^{IN}/NT		-0.007	-0.261	-0.486		-0.071	0.320	-0.590		

Table 3 First-order autoregressive tests.

$$r_t = \alpha_0 + \left(\sum_{i=1}^5 \alpha_i D_{i,t} + \beta_{SL} \frac{NS_{t-1}^{SL}}{NT_{t-1}} + \beta_{LL} \frac{NS_{t-1}^{LL}}{NT_{t-1}} + \beta_{IN} \frac{NS_{t-1}^{IN}}{NT_{t-1}} \right) r_{t-1} + \delta_1 \frac{NS_t}{NT_t}$$

where $D_{i,t}$ are the day-of-the-week dummy variables; NT is the total number of trades; NS^{SL} , NS^{LL} and NS^{IN} are the number of sells by small liquidity traders, large liquidity traders, and informed traders, respectively; and NS is the sum of NS^{SL} , NS^{LL} , and NS^{IN} . α_i are not reported. T -statistics using the heteroscedasticity-robust standard error are reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent level, respectively. Liquidity-based transactions that trades more than k contracts (where $k = 1, 4, 9, \text{ and } 12$) are considered as large liquidity orders, otherwise, small liquidity orders.

	Number of transactions				Number of contracts			
	k=1	k=4	k=9	k=12	k=1	k=4	k=9	k=12
β_{SL}	-0.61 (-0.32)	-0.71 (-0.46)	-1.10 (-0.80)	-1.64 (-1.26)	5.71 (1.08)	2.59 (1.36)	0.80 (0.80)	-0.28 (-0.37)
β_{LL}	-2.73 (-1.98)**	-3.49 (-2.33)**	-5.27 (-2.64)***	-7.84 (-2.31)**	-1.04 (-1.82)*	-1.27 (-2.19)**	-1.57 (-2.56)**	-1.70 (-2.43)**
β_{IN}	-1.47 (-0.63)	-2.12 (-0.89)	-3.05 (-1.22)	-3.38 (-1.29)	1.31 (0.88)	0.61 (0.39)	0.29 (0.18)	0.62 (0.38)
δ_1	3.86 (1.86)*	3.74 (1.80)*	3.55 (1.71)*	3.56 (1.71)*	-14.27 (-13.88)***	-14.34 (-13.97)***	-14.38 (-14.01)***	-14.28 (-13.92)***
n	755	755	755	755	755	755	755	755
R²	0.03	0.03	0.03	0.03	0.23	0.23	0.24	0.23

Table 4 ACG's asymmetric volatility tests

$$r_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 \frac{NS_t}{NT_t} + \sum_{i=1}^{10} \lambda_i r_{t-i} + \varepsilon_t \quad (2.0)$$

$$y_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \phi_0 \varepsilon_{t-1} + e_t \quad (2.1)$$

$$y_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \left(\phi_0 + \phi_1 \frac{NS_{t-1}}{NT_{t-1}} \right) \varepsilon_{t-1} + e_t \quad (2.2)$$

$$y_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \left(\phi_0 + \phi_1^+ \frac{NS_{t-1}}{NT_{t-1}} (\varepsilon_{t-1} \geq 0) + \phi_1^- \frac{NS_{t-1}}{NT_{t-1}} (\varepsilon_{t-1} < 0) \right) \varepsilon_{t-1} + e_t \quad (2.3)$$

where r_t is the price returns, y_t is the log realized volatility, $D_{i,t}$ are the day-of-the-week dummy variables, NT is the total number of trades, NS is the total number of sells, $(\varepsilon_{t-1} \geq 0)$ is an indicator variable taking on value of 1 if ε_{t-1} is equal or greater than zero, and $(\varepsilon_{t-1} < 0)$ is one if ε_{t-1} is negative.

Trading activity is measured by the number of transactions and the number of contracts. The table reports only estimates of ϕ 's from Eq. (2.1), (2.2), and (2.3). T -statistics using the heteroscedasticity-robust standard error are reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent level, respectively.

	Number of transactions			Number of contracts		
	Eq. (2.1)	Eq. (2.2)	Eq. (2.3)	Eq. (2.1)	Eq. (2.2)	Eq. (2.3)
ϕ_0	-0.006 (-2.33)**	0.084 (1.79)*	0.079 (1.70)*	-0.008 (-2.58)**	0.066 (2.38)**	0.059 (2.14)**
ϕ_1		-0.179 (-1.92)*			-0.151 (-2.68)***	
ϕ_1^+			-0.134 (-1.44)			-0.107 (-1.84)*
ϕ_1^-			-0.202 (-2.19)**			-0.165 (-2.93)***
n	746	746	746	746	746	746
R²	0.879	0.880	0.883	0.861	0.862	0.864
Adj. R²	0.877	0.878	0.880	0.858	0.859	0.860

Table 5 Asymmetric Volatility Tests with Trader Classification.

$$r_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 \frac{NS_t}{NT_t} + \sum_{i=1}^{10} \lambda_i r_{t-i} + \varepsilon_t \quad (2.0)$$

$$y_t = \alpha_0 + \sum_{i=1}^4 \alpha_i D_{i,t} + \omega_0 NT_t + \sum_{i=1}^{10} \rho_i y_{t-i} + \left(\phi_0 + \phi_{SL} \frac{NS_{t-1}^{SL}}{NT_{t-1}} + \phi_{LL} \frac{NS_{t-1}^{LL}}{NT_{t-1}} + \phi_{IN} \frac{NS_{t-1}^{IN}}{NT_{t-1}} \right) \varepsilon_{t-1} + e_t \quad (2.4)$$

where r_t is the price returns, y_t is the log realized volatility, $D_{i,t}$ are the day-of-the-week dummy variables; NT is the total number of trades; NS^{SL} , NS^{LL} , and NS^{IN} are the numbers of sells by small liquidity traders, large liquidity traders, and informed traders, respectively. Trading activity is measured by the number of transactions and the number of contracts. The table reports only estimates of ϕ 's from Eq. (2.4). T -statistics using the heteroscedasticity-robust standard error are reported in parentheses. ***, **, and * indicate statistical significance at 1, 5, and 10 percent level, respectively. The results are estimated using different cutoffs ($k = 1, 4, 9, 12$) to separate large and small liquidity orders.

	Number of transactions				Number of contracts			
	k=1	k=4	k=9	k=12	k=1	k=4	k=9	k=12
ϕ_0	0.068 (1.38)	0.071 (1.44)	0.072 (1.46)	0.069 (1.41)	0.104 (3.20)***	0.094 (3.02)***	0.085 (2.76)***	0.080 (2.62)***
ϕ_{SL}	-0.118 (-0.83)	-0.173 (-1.52)	-0.185 (-1.81)*	-0.182 (-1.89)*	-1.374 (-2.79)***	-0.623 (-3.53)***	-0.347 (-3.76)***	-0.274 (-3.80)***
ϕ_{LL}	-0.188 (-1.88)*	-0.169 (-1.56)	-0.133 (-0.94)	-0.054 (-0.22)	-0.147 (-2.56)**	-0.115 (-1.94)*	-0.091 (-1.45)	-0.049 (-0.70)
ϕ_{IN}	-0.040 (-0.23)	-0.031 (-0.18)	-0.009 (-0.05)	0.014 (0.07)	-0.158 (-1.16)	-0.085 (-0.59)	-0.069 (-0.47)	-0.044 (-0.29)
n	746	746	746	746	746	746	746	746
R²	0.880	0.880	0.880	0.880	0.863	0.864	0.863	0.864
Adj. R²	0.877	0.877	0.877	0.877	0.860	0.860	0.860	0.860

Figure 1 Average selling activity associated with different level of return shocks.

We divide our sample into positive- and negative-return shock subsamples. For each subsample, we further divide the return shocks by sizes into 4 bins according to the subsample quartile. Respectively, bins -4 to -1 (1 to 4) contain observations in size quartile 1 to 4 of the negative (positive) return shock subsample and are shown on x-axis. Based on observations in each bin, the average selling activity (less the sample mean) for each trader type is calculated and plotted on the y-axis. The selling activity is defined as the number of contracts sold by small liquidity traders divided by the number of total contracts traded.

