Volatility Information Trading in the Option Market

Sophie Xiaoyan Ni, Jun Pan, and Allen M. Poteshman[*]

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Abstract

Investors can trade on positive or negative information about firms in either the stock or the option market, and a well-developed literature examines the use of options to make directional trades. Surprisingly, very little is known about option market trading on volatility information, despite the fact that options are uniquely suited for such trading. This paper investigates volatility trading in the equity option market. Two principal predictions of the hypothesis that investors bring volatility information to the option market are that net non-market maker demand for volatility is positively related to the future volatility of underlying stocks and that market makers protect themselves from informed volatility traders by raising (lowering) option prices in response to increases (decreases) in net volatility demand. Using a dataset that allows us to construct net non-market maker demand for volatility at the Chicago Board Options Exchange over the 1990 through 2001 period, we find strong empirical support for both of these predictions. We also present two additional results which each provide further confirmation for the proposition that investors bring volatility information to the option market. First, non-market maker net volatility demand constructed from transactions which open new option positions is a stronger predictor of the future volatility of underlying stocks than net volatility demand constructed from transactions which close existing option positions. Second, the impact on option prices from each unit of net non-market maker volatility demand significantly increases as informational asymmetry intensifies in the days leading up to earnings announcement dates.

[*] Ni and Poteshman are at the University of Illinois at Urbana-Champaign, xni@uiuc.edu and poteshma@uiuc.edu. Pan is at the MIT Sloan School of Management and NBER, junpan@mit.edu. We thank Joe Levin, Eileen Smith, and Dick Thaler for assistance with the data used in his paper. We benefited from discussions with Joe Chen, Jun Liu, Josh Pollet, Dimitri Vayanos, Jiang Wang, and Josh White.

1. Introduction

The last several decades have witnessed astonishing growth in the market for derivatives. Its current size of $200 trillion is more than 100 times greater than thirty years ago [Stulz (2004)]. Accompanying this impressive growth in size has been an equally impressive growth in variety: the derivatives market now extends to a broad spectrum of risk including equity risk, interest-rate risk, weather risk, and, most recently, credit risk and inflation risk. The economic value of derivatives has been an important driver of their phenomenal growth. While financial theory has traditionally emphasized the spanning properties of derivatives and their consequent value in improving risk-sharing [Arrow (1964) and Ross (1976)], the role of derivatives as a vehicle for the trading of informed investors has emerged as another important economic function of these securities [Black (1975) and Grossman (1977)].

In this paper, we contribute to the body of knowledge on the economic value of derivatives by investigating the role of options as a venue for trading on information about equity volatility. Our focus on informed volatility trading is motivated to a large extent by the fact that equity options are uniquely suited to investors with information about future volatility. In particular, unlike traders with directional information about underlying stock prices who can trade in either the stock or option markets, traders with volatility information can only use non-linear securities such as options. While the empirical relationship between option volume and the future direction of underlying stock prices has been examined in some detail [Stefan and Whaley (1990), Amin and Lee (1997), Easley, O'Hara, and Srinivas (1998), Chan, Chung, and

Fong (2002), Cao, Chen, and Griffin (2005), and Pan and Poteshman (2005)],[1] little is known about whether option volume is informative for the future volatility of underlying stocks.

We investigate this issue using a unique dataset from the Chicago Board Options Exchange (CBOE) that records purchases and sales of put and call options by non-market makers. We construct from these data daily net non-market maker demand for volatility on each underlying stock from all equity options traded at the CBOE over the 1990-2001 period and find that option market demand for volatility is a statistically significant predictor of the future realized volatility of underlying stocks. The predictability lasts up to one week into the future and is robust to different measures of realized volatility and to controlling for directional information in the option volume. A natural interpretation of this evidence that option volume is informative about future volatility is that investors trade on volatility information in the option market and the information subsequently is reflected in the underlying stocks.

This interpretation is corroborated by our finding that the net demand for volatility constructed from open option volume — trades initiated by non-market makers to open new option positions — has much stronger predictability, in both magnitude and statistical significance, than the net demand constructed from close option volume. While both open and close trades can be informationally motivated, the informational content from close trades is expected to be lower, because traders can only use information to close positions if they happen to have appropriate positions open at the time they become informed. The stronger predictability from the net demand constructed from open volume is, therefore, consistent with the

[1] Pan and Poteshman (2005) demonstrate convincingly that option volume contains information about the future direction of underlying stock prices. In another recent paper, Chakravarty, Gulen, and Mayhew (2004) examine the temporal relationship between price movements in the stock and the option markets and show that a portion of price discovery occurs in the option market.

predictability we identify having its economic source in volatility information trading in the option market.

The second major issue that we investigate is the link between informational asymmetry and the impact of volatility demand on option prices. Pre-scheduled earnings announcements are exogenous information events, and in the period leading up to earning announcements days (EADs) option market makers face increasing informational asymmetry. While there will be informational asymmetry about both the directional move and the volatility of the underlying stock price at the EAD, the asymmetry about volatility information is likely to be of more concern to option market makers. The reason is that the market makers can delta-hedge (with the underlying stock) the risk associated with the directional move, but collectively they must bear the volatility risk. Moreover, informed traders with directional information can trade in either the option or the stock market, while traders with volatility information can only trade in the option market.

We find that the net demand for volatility impacts option prices and that the price impact per unit of volatility demand steadily increases in the period leading up to EADs.[2] For example, two days and one day before EADs, the price impact per unit of volatility demand increases by, respectively, 50% and 55% from its average level. On EADs and the days following EADs, the additional price impact diminishes and becomes statistically insignificant. Since the time variation in the price impact mirrors the time variation in informational asymmetry, this evidence

[2] Bollen and Whaley (2004) also show that the net demand for volatility impacts option prices but do not investigate variation in the impact around EADs.

is consistent with market makers protecting themselves from option market trades motivated by volatility information.[3]

The rest of the paper is organized as follows. Section 2 develops our empirical specifications, Section 3 details the data, Section 4 presents the results, and Section 5 concludes.

2. Empirical Specification

The first part of our empirical investigation examines whether option volume possesses information about the future volatility of underlying stocks. If informed investors indeed bring private information about future volatility to the option market, then one would expect the net option market volatility demand from non-market makers to be positively related to the future volatility of underlying stocks.

We construct the demand for volatility from the market maker's perspective and separate trading volume into non-market maker buys and sells of call and put options. Given that both call and put options have positive "vega" (exposure to volatility), we consider buy volume for both call and put options as positive demand for volatility and sell volume as negative demand for volatility. Specifically, for each stock *i* and on day *t*, the demand for volatility is measured by

$$D_{i,t} \equiv Buy_{i,t}^{c} - Sell_{i,t}^{c} + Buy_{i,t}^{p} - Sell_{i,t}^{p}, \tag{1}$$

where $Buy_{i,t}^{c}$ is the total volume of non-market maker call purchases across all strike prices and times to expiration, and $Sell_{i,t}^{c}$ is the total volume of non-market maker call sales across all strike prices and times to expiration. $Buy_{i,t}^{p}$ and $Sell_{i,t}^{p}$ are the similar quantities for put options.[4]

[3] It is also interesting to note that the predictive power of net volatility demand more than doubles on the day before EADs compared to the average level of one-day ahead predictability. This result is consistent with the hypothesis that volatility demand contains more information on the days leading up to EADs.

We test whether the net non-market maker option market demand for volatility predicts the future volatility of underlying stocks by estimating the following specification:

$$\begin{aligned} OneDayRV_{i,t} &= a + b_j D_{i,t-j} + c_j D_{i,t-j} Ind_{i,t} + d_j OneDayRV_{i,t-1} + e_j OneDayRV_{i,t-1} Ind_{i,t} \\ &\quad + f_j \ln\left(stkVolume_{i,t-j}\right) + g_j \ln\left(stkVolume_{i,t-j}\right) Ind_{i,t} + \varepsilon_{it}, \end{aligned} \tag{2}$$

where $OneDayRV_{i,t}$ is a proxy for the realized volatility of stock *i* on date *t*, Ind_{it} is 1 if *t* is an EAD for stock *i* and otherwise is zero, and $stkVolume_{i,t}$ is the number of shares of stock *i* that trade on day *t*. For a fixed *j*, the regression specification in equation (2) uses the net demand for volatility at time $t-j$ to predict the *j*-day ahead realized stock volatility. According to the hypothesis that there is volatility information trading in the option market, we would expect b_j to be positive and significant for at least some of the j-day ahead predictive regressions. Moreover, assuming that informed traders on average possess more information about what will occur at EADs than non-EADs, we would expect to see an incremental predictability from demand for volatility which would be captured by a positive slope coefficient c_j on the interaction term in equation (2). When an earnings announcement occurs after the market closes, the volatility is actually realized on the day after the earnings announcement. Hence, we also perform the test in equation (2) with Ind_{it} defined as 1 if *t* is the day after the EAD for stock *i*. The terms involving $OneDayRV_{i,t}$ control for GARCH type volatility clustering and the terms involving $stkVolume_{i,t-j}$ control for any relationship between stock volume and future volatility and also for the possibility that stock volume is correlated with option net demand. Clearly,

[4] In addition to simply aggregating the option volume across all strike prices and times to expiration to obtain volatility demand, we will also sometimes use vega-weighted option volume to obtain an alternative measure of volatility demand. The rationale behind such a measure is that options with various strike prices and times to expiration have different exposure to volatility, and the ones with higher vega should count more toward the total volatility demand.

investors trade options for reasons other than possessing private information about the volatility of underlying stocks (e.g., as a result of directional information, for hedging, or for liquidity reasons). This fact should just make it more difficult to detect a relationship between option volume and the future volatility of underlying stocks.

The second part of our empirical investigation is motivated to a large extent by the voluminous literature that examines the asset pricing implication of informational asymmetry.[5] In particular, the seminal paper of Kyle (1985) provides the theoretical framework crucial for our empirical study. In the single-auction setting of Kyle (1985), the *ex post* liquidation value of the risky asset, denoted $\tilde{v}$, is normally distributed with mean p_0 and variance Σ_0. The quantity traded by noise traders is denoted $\tilde{u}$, which is normally distributed with mean zero and variance σ_u^2 and is independent of $\tilde{v}$. The informed trader observes $\tilde{v}$ but not $\tilde{u}$ and trades strategically with quantity $\tilde{x}$ to maximize his profit. The market maker observes the combined quantity $\tilde{x}+\tilde{u}$ and sets price $\tilde{p}=E\left(\tilde{v}\middle|\tilde{x}+\tilde{u}\right)$, conditioning on his information.

Key to our empirical specification is the following equilibrium solution of Kyle (1985):

$$\tilde{p}=p_0+\lambda\left(\tilde{x}+\tilde{u}\right), \tag{3}$$

where $\lambda=2\left(\Sigma_0/\sigma_u^2\right)^{1/2}$. By definition, λ increases with the information advantage of the informed trader Σ_0 and decreases with the level of noise trading σ_u. This implies that the market maker is more likely to face "bad trades" (i.e., trades from the informed trader) when λ is higher. To protect himself from increased adverse selection from informed traders, the market maker increases the sensitivity of the price $\tilde{p}$ to the total trade quantity $\tilde{x}+\tilde{u}$ and thereby makes the market less liquid. The price-quantity relation in equation (3) is a result of this process. In

[5] See O'Hara (1995) for a comprehensive review of the literature.

particular, λ, also known as Kyle's lambda, controls how sensitive the equilibrium price is to demand. Intuitively, a higher level of informational asymmetry results in heightened price impact.

Our empirical design builds on this important intuition of Kyle's model. Our focus is on an aspect of informational asymmetry that is unique to the option market: private information about volatility and volatility information trading. Translating Kyle's model to our equity option setting, our first task is to use options to construct securities with the highest sensitivity to the realization of equity volatility and the lowest sensitivity to the directional moves in the underlying stock. We do so by forming near-the-money straddles. On each day t and for each stock i, we pick a pair of call and put options with the same time to expiration and the same strike price that is as close to the money as possible. While both call and put options increase in value with increasing volatility, their respective sensitivity to the underlying stock movement is opposite in sign, and equal in magnitude if both options are at-the-money (ATM). By adding such pairs of options to form a straddle, we are therefore closer to a "clean" security on volatility. In practice, however, we are using exchange-traded options, whose available moneyness and time-to-expiration vary over time. To minimize the effect of moneyness and time-to-expiration, we measure the straddle price in term of Black-Scholes implied volatility. Specifically, we convert the market-observed call and put option prices into their respective Black-Scholes implied volatility, IV_{it}^{c} and IV_{it}^{p}, and use

$$IV_{it} = \frac{1}{2}\left(IV_{it}^{c} + IV_{it}^{p}\right) \tag{4}$$

as the risky asset $\tilde{p}$ in the Kyle model.

We would also like to obtain a measure of ex-ante expected volatility, which is similar in spirit to p_0 in Kyle's model. This variable, however, is hard to measure, and we use the *ex post* realized volatility as a proxy. On day *t* for stock *i*, let T_{it} be the time to expiration, measured in trading days, for the chosen straddle. We calculate realized volatility over the life of this straddle by

$$RV_{it} = \left(\frac{250}{T_{it}} \sum_{j=1}^{T_{it}} r_{i,t+j}^2 \right)^{1/2}, \tag{5}$$

where $r_{i,t}$'s are daily stock returns (after subtracting the average daily return over the life of the straddle). Our trade day *t* measure of deviation of option prices on stock *i* from fundamental value will then be $IV_{it} - RV_{it}$. This quantity can be regarded as the analog to $\tilde{p} - p_0$ in the Kyle model. Although there is some uncertainty about which option pricing model should be used to imply volatility, we will mitigate this problem by focusing on daily differences in $IV - RV$.

Our empirical testing focuses on the fact that the economic source of Kyle's lambda is informational asymmetry. In particular, a higher level of informational asymmetry results in a higher level of price impact. Although it is hard to measure directly the level of informational asymmetry, the days leading up to earnings announcements constitute natural exogenous events for which the level of informational asymmetry is likely to be increasing. While there may be informational asymmetry about either the directional move of the underlying stock price or about its volatility, the informational asymmetry with respect to volatility is likely to be of more concern to option market makers. In contrast to the risk associated with the directional move, which can be delta-hedged using the underlying stock, the volatility shock is a risk that in aggregate the market makers have to bear. Moreover, informed traders with directional information can trade in either the option or the stock market, while informed traders with volatility information can trade only in the option market.

The empirical specification to investigate the impact of volatility demand is as follows:

$$\begin{aligned} & IV_{it} - RV_{it} - \left(IV_{it-1} - RV_{it-1}\right) \\ & \quad = \alpha + D_{it}\left(\lambda + \lambda_{-5}^{EAD} Ind\left(EAD-5\right)_{it} + \ldots + \lambda_{0}^{EAD} Ind\left(EAD-0\right)_{it} + \ldots + \lambda_{+5}^{EAD} Ind\left(EAD+5\right)_{it}\right) \\ & \qquad + \alpha_{-5}^{EAD} Ind\left(EAD-5\right)_{it} + \ldots + \alpha_{0}^{EAD} Ind\left(EAD-0\right)_{it} + \ldots + \alpha_{+5}^{EAD} Ind\left(EAD+5\right)_{it} + \varepsilon_{it}, \end{aligned} \quad (6)$$

where the $Ind\left(EAD-n\right)_{it}$ variable is 1 if trade day $t+n$ is an EAD for stock *i* and otherwise is 0. For example, $Ind\left(EAD-5\right)_{it}$ is 1 if *t* is 5 trade days before an EAD for stock *i* and otherwise is 0.

The main objective of this empirical specification is to test the hypothesis that increased informational asymmetry is associated with increased price impact. Specifically, the slope coefficient λ in equation (6) captures the average price impact for one unit increase of volatility demand. Kyle's model predicts that this coefficient will be positive. To link the price impact to its economic source of informational asymmetry, however, we focus on the more important part of our empirical test. Specifically, λ_{τ}^{EAD} for $\tau = -5,\ldots,-1,0,1,\ldots,5$ captures the *incremental* price impact of volatility demand around EADs. In particular, we expect λ^{EAD} to be positive and significant on days leading to the EAD, but not for the days after the EAD, when information has already been released. The (uninteracted) $Ind\left(EAD-n\right)_{it}$ variables are included to control for any systematic daily changes in $IV-RV$ around EADs which are unrelated to volatility demand. Consequently, the α_{τ}^{EAD} coefficients for $\tau = -5,\ldots,-1,0,1,\ldots,5$ capture price impact around EADs which is unrelated to volatility demand.

3. Data

This section describes data sources, sets out the criteria for selecting observations for the regressions specified in the previous section, and provides summary statistics for the variables that appear in the regressions.

3.1 Data sources

The data in this paper are drawn from a number of sources. The data used to compute volatility demand are obtained directly from the CBOE. This data set contains daily non-market maker volume for all CBOE listed options over the period January 2, 1990 through December 31, 2001. For each option, the daily trading volume is subdivided into four types of trades: "open-buys" in which non-market makers buy options to open new long positions, "open-sells" in which non-market makers sell options to open new written option positions, "close-buys" in which non-market makers buy options to close out existing written option positions, and "close-sells" in which non-market maker sell options to close out existing long option positions.[6] When calculating the demand variable defined in equation (1), the buy volume is the sum of the open-buy and close-buy volume and the sell volume is the sum of the open-sell and close-sell volume.

Over the period January 2, 1990 through January 31, 1996 we get option price data from the Berkeley Options Database, and from February 1, 1996 through December 31, 2001 we get price and implied volatility data from OptionMetrics. For the first part of the data period (i.e., through January 1996), we compute daily option implied volatilities from the midpoint of the last bid-ask price quote before 3:00 PM Central Standard Time. In particular, we use the dividend-adjusted binomial method with the 1 month LIBOR rate as a proxy for the risk-free rate and the

[6] The non-market maker volume is also subdivided into four classes of investors (proprietary traders and three types of public customers.) We do not make use of this subdivision, because our main interest is the response of market makers to the aggregate volume that they face.

actual dividends paid over the life of an option as a proxy for the expected dividends. Starting in February 1996, we use the implied volatilities supplied by OptionMetrics which are computed in a similar way.

Stock prices, returns, volumes, and dividends during the entire sample period are obtained from the Center for Research in Security Prices (CRSP). Earning's announcement dates are obtained from Compustat.

3.2 Observation Selection

In order for there to be an observation when estimating regression specification (2) for an underlying stock *i* on trade date *t*, there must be data available to construct option volatility demand for stock *i* on trade date $t-j$. In order for there to be an observation when estimating regression specification (6) for an underlying stock *i* on a trade date *t*, there must be data available to construct option volatility demand for stock *i* on trade date *t* and to construct the daily change in implied volatility for underlying stock *i* from trade date $t-1$ to trade date *t*.

Volatility demand is considered to be available for underlying stock *i* on day *t* if there are at least 50 contracts of buy and sell trading volume by non-market-maker investors for options with time to expiration between 5 and 50 trading days and ratio of strike price to closing stock price between 0.80 and 1.20. The data to construct the daily change in implied volatility for stock *i* on trade date *t* is available if there are a call and a put on stock *i* on trade date *t* that have the same strike price and time to expiration which meet all three of the following conditions: (1) both the call and put have strictly positive trading volume and implied volatility data available on day $t-1$ and day *t*,[7] (2) the time to expiration of the call and the put is between 5 and 50 trading

[7] Through January 1996 we use the Berkeley Option Database to determine whether an option traded. Beginning in February 1996 we use OptionMetrics to determine whether an option traded.

days, and (3) the ratio of the strike price to the closing stock price on day *t* is between 0.80 and 1.20. If there is more than one put-call pair satisfying the above three conditions, we choose the pair whose strike price is nearest to the closing stock price on day *t*. If there is still more than one put-call pair, the pair with the shortest maturity is selected. After selecting the put-call pair, we calculate the change of implied volatility by subtracting the average call and put implied volatilities on day $t-1$ from the average on day *t*.

For specification (6), we de-mean the dependent (i.e., change in implied volatility minus realized volatility) variable for each underlying stock *i* by subtracting its calendar year mean. We normalize each stock's volatility demand by subtracting its calendar year mean and then dividing by its calendar year standard deviation. Stocks with fewer than 25 time-series observations in a calendar year are deleted for that year.

Altogether, we have 288,135 stock-days and 2,039 different stocks over our twelve year period. There are 6,005 stock-days which fall on earnings announcement dates (EADs) and 1,307 different stocks have observations on at least one EAD. There are an average of 97 stocks on each trading day. We also rank selected stocks into small, medium, and large size terciles on each trading day. The median market capitalization for the small tercile stocks falls into the fifth decile of NYSE stocks which reflects the fact that stocks with active option trading tend to be larger than average. The median market capitalization for our medium (large) size tercile stocks fall into the ninth (tenth) size decile of NYSE stocks.

3.3 Summary Statistics

Table 1 contains the summary statistics for the variables used in our tests. The average implied volatility is 6446 basis points (i.e., 64.46%) for all observations. Although not reported in the table, the average implied volatility for the small (large) tercile of underlying stocks is 8298 (4725) basis points. The average realized volatility for the whole sample is 6156 basis points, 290 basis points lower than average implied volatility. Quite reasonably, realized volatility is more variable than implied volatility. Indeed, the standard deviation of realized volatility is about 1000 basis points higher than that of implied volatility. Both implied and realized volatility exhibit strong positive autocorrelation and positive skewness. Realized volatility has higher skewness and kurtosis than implied volatility.

The next two variables in Table 1 are the daily changes in implied and realized volatility. Both variables have a small negative mean. The means may be negative because of the negative skewness in the distribution of the variables, especially for realized volatility. Note in particular that the absolute values of the minima are much larger than for the maxima.

The fifth and sixth variables in Table 1 measure the daily change in the spread of implied volatility over realized volatility. That is, they are the difference between the change in implied volatility from day $t-1$ to day t and the change in realized volatility from day $t-1$ to day t. The first of these variables is simply this difference and the second is this difference divided by the day $t-1$ implied volatility. Both of these variables have small positive average values. Unreported results show that the positive averages are larger (smaller) for smaller (larger) underlying stocks.

Table 1 also reports descriptive statistics for daily straddle returns. On average, the straddle returns are –446 basis points which is consistent with other studies which show that straddles usually earn negative returns which are large in magnitude. The average absolute daily return for underlying stocks is about 330 basis points. This number is higher than the average daily absolute return for all stocks, because of the requirements that the call and the put both trade on day $t-1$ and day t and that the non-market maker aggregate option volume on day t is at least 50 contracts. These requirements tend to select underlying stocks when they have larger than average absolute stock price movements.

The volatility demand has a negative mean which implies that on average market makers are long volatility. We also break volatility demand into net bought call volume and net bought put volume, where net bought call (put) volume is non-market-maker bought call (put) volume minus non-market-maker sold call (put) volume. If the volatility demand variable correctly measures investors trading on volatility, then there should not be large differences between net bought call volume and net bought put volume, since volatility trading involves buying or selling calls and puts in equal measure. Table 1, indeed, shows similar net bought call and net bought put trading. In contrast to volatility demand, net bought open volume, which is non-market maker open buy option volume minus non-market maker open sell option volume, is positive. We also break net bought open volume into net bought open call volume and net bought open put volume. The mean difference between net bought open call and put volume also is not large.

Table 2 reports the cross-sectional correlation coefficients for the main variables in Table 1. Both implied volatility (IV) and realized volatility (RV) are positively correlated with absolute stock returns and stock volume. The correlation coefficients are 0.25 and 0.32 for implied volatility, and 0.17 and 0.16 for realized volatility. On the other hand, their correlation with volatility demand is close to zero.

Daily change in implied volatility (dIV) and daily change in realized volatility (dRV) are positively related to straddle returns. The correlation coefficient for change in implied volatility (0.36) is higher than that for change in realized volatility (0.13). It is worth noting that the daily change in implied volatility has a substantial positive correlation with both volatility demand

(0.25) and net bought open volume (0.20), while the correlation of daily change in realized volatility with these variables is close to zero. Hence, the positive correlation between volatility demand and change in implied volatility minus change in realized volatility is not due to co-movement between volatility demand and realized volatility. In other words, it appears that volatility demand may drive implied volatility away from the actual volatility of underlying stocks. Another difference between change in implied volatility and change in realized volatility is their correlation with absolute stock returns. For change in implied volatility, the correlation coefficient is only 0.04, but for change in realized volatility the correlation is –0.80. Accordingly, on average large stock price movements are not associated with either increases or decreases in forward looking implied volatility. For realized volatility, on the other hand, large stock price movements are associated with decreases in realized volatility over the remaining life of the option. It is not clear why implied volatility does not reflect this fact.

Table 2 also indicates that the two measures of daily difference in the changes of implied and realized volatility, dIV-dRV and (dIV-dRV)/IV are positively correlated with volatility demand and net bought open volume. These positive correlations are another sign that volatility demand may drive implied volatility away from the volatility that will be realized over the life of the option.

Figure 1 depicts the average values of the main variables leading up to, on, and after EADs. In this figure, day 0 is an EAD, and date –10 (date +10) is 10 trading days before (after) an EAD. The horizontal line in each plots is the average value of the variable across all observations. The first panel shows that before EADs, daily changes in implied volatility are all positive. The largest average daily change of about 100 basis points occurs one day before the EAD. From day 0 through day 10, the daily changes in implied volatility are all negative. The day after the EAD is the most negative with a value of about –300 basis points. As we move further after the EAD, the bars remain negative but with decreasing magnitude. After about a week, the bars are not far from the sample mean. Panel 2 of Figure 1 displays the results for the change in realized volatility. Before the EAD, the realized volatility changes are mostly above the sample mean. On the EAD and the day after the EAD (i.e., on day 0 and day 1), there is a significant reduction in realized volatility of around –300 and –550 basis points respectively. These reductions imply that there are large stock price movements on these days.

The third panel of Figure 1 shows daily changes in the spread of implied volatility over realized volatility (normalized by the overall level of volatility). The change in the spread before EADs are above the sample mean, while 2 or more days after the EADs the changes in the spread are below the sample mean. It should be noted that from 5 days before the EAD up through the EAD, the change in the spread of implied volatility over realized volatility increases. Interestingly, the volatility demand depicted in Panel 4 in Figure 1 also monotonically increases leading up to the EAD. The plot also suggests that investors tend to be long volatility before EADs and short volatility after EADs.

The last two panels in Figure 1 are for absolute stock return and stock volume. Absolute stock returns tend to be higher before EADs, and the highest absolute stock returns are on the EAD and the day after the EAD. Stock volumes are highest on the same days. It is interesting that even though absolute stock returns are above sample mean before EADs, pre-EAD stock volumes are below the sample mean except for on day –1. This is consistent with a decrease in stock market liquidity when information asymmetry increases leading up to EADs.

4. Results

4.1 Information in option volume for future stock price volatility

As detailed in Section 2, our first empirical specification is designed to test whether net non-market maker demand for volatility in the option market predicts the future volatility of underlying stocks. We estimate equation (2) on each trade day after filtering observations and normalizing variables as described in Section 3.

Table 3 presents the results of estimating specification (2) for $j = 1, 2, 3, 4,$ and 5. As above, we run pooled regressions and compute *t*-statistics from robust standard errors which correct for cross-sectional correlation in the data. The $OneDayRV_{i,t}$ proxy that we use for the realized volatility of stock *i* on date-*t* is 10,000 times stock *i*'s high minus low price during day *t* divided by stock *i's* closing price on date-*t*-1.[8] Panel A reports the results when both open and close option volume are used to compute the net demand variable, $D_{i,t-j}$. For all values of *j*, the coefficient on the net volatility demand variable is positive and highly significant. These results indicate that option volume contains information about the future volatility of the underlying stock for at least five trade days into the future. The coefficient on the interaction of the demand variable with the indicator that trade day *t* is an EAD is also positive and significant for all five values of *j*. Hence, leading up to EADs each unit of volatility demand contains more information about what the volatility will be on the EAD than it does ahead of non-EAD days. This finding supports the proposition that leading up to EADs there is more asymmetry with respect to volatility information than at other times.

[8] The results in this subsection are robust to defining the realized volatility proxy in a number of ways including simple absolute daily return, the log of the intraday high minus the log of the intraday low, and the log of the difference between the intraday high and low.

The coefficient on the control variable which proxies for the realized volatility on day $t-1$ is positive and highly significant. This is not surprising, since it is well known from the ARCH/GARCH literature that equity volatility clusters. It should be noted, however, that by including this control variable, our results show that the volatility demand on day $t-j$ predicts the idiosyncratic volatility on day *t*. That is, this control variable rules out the possibility that volatility demand on day $t-j$ has idiosyncratic information about volatility only for some day before *t* which is carried forward to day *t* through a volatility clustering mechanism.[9]

Since our dataset distinguishes non-market maker volume which opens new option positions from non-market maker volume which closes existing positions, we have the opportunity to investigate separately the net volatility demand from opening and closing volume. Panels B and C of Table 3 report estimation results when the net volatility demand is computed from only, respectively, opening or closing option volume. The main effect is considerably stronger for opening than for closing volume. For example, when $j=1$ the coefficient on net volatility demand is 9.61 [*t*-statistic = 15.29] and the coefficient on the net demand interacted with the EAD indicator is 28.82 [*t*-statistic = 8.31]. On the other hand, when close volume is used, the corresponding coefficient estimates are just 3.83 [*t*-statistic = 5.76] and 7.18 [*t*-statistic = 1.93].

These results are interesting for two reasons. First, we would expect that investors who trade on volatility information in the option market are more likely to do so by opening new option positions – in order to do so by closing existing option positions, a trader who obtains private volatility information would need to already have existing option positions on the

[9] In unreported results, we also estimated this specification when the realized volatility proxy control variables were measured at time $t-j$ rather than at time $t-1$. This had little impact on the point estimates or *t*-statistics for the volatility demand variables.

underlying stock which the information dictates should be closed out. Second, the fact that the main result is considerably stronger for opening than closing volume suggests that mechanical mechanisms such as market maker hedging are unlikely to account for much of the observed future changes in the volatility of the underlying stocks.[10] Since market makers (and other participants) do not know whether their counter parties are opening or closing option positions with their trades, they will treat both open and close volume in the same way. As a result, any mechanical effects should impact the open and the close volume equally. For both of these reasons, the fact that the main result is much stronger for the open than the close volume provides evidence that it is driven by investors bringing private volatility information to the market rather than by some other mechanism.

Pan and Poteshman (2004) show that option volume, in particular open buy put-call ratios, contains information about the future direction of underlying stock price movements. Hence, one might be concerned that the positive relation between option volume net demand and future stock price volatility is driven by investors trading on directional information in the option market. This could occur, for example, if investors with positive information about an underlying stock bought calls and the stock price subsequently increased. The call purchase would increase the net demand variable while the later increase in stock price would increase the measure of future realized volatility. For negative information, the purchase of puts would also increase the net demand variable while the later decrease in stock price would increase the measure of future realized volatility as well.

To investigate whether option market trading on directional information is likely to be an important factor in the previous results, we re-run the tests from Table 3 separately on underlying

[10] Since market makers nearly always hedge their option positions on the same day that they are taken, any volatility in the underlying stock caused by hedging should be concentrated on day $j = 0$ anyway.

stocks that are in the bottom, middle, and top tercile of open buy volume put-call ratio. That is, on each trade day we rank underlying stocks on their open buy volume put-call ratio and then run three cross-section regressions each day, one on each tercile of stocks. We do this, because Pan and Poteshman (2004) show that the open buy put-call ratio is a strong predictor of the direction of future movements of underlying stock prices. If investors bringing directional information to the option market plays an important role in generating the results reported in Table 3, then we would expect the findings to be weaker for the middle tercile stocks (for which there is little directional information in the option volume) and stronger in the low (high) tercile stocks which contain a good deal of information that stock prices are going to subsequently increase (decrease).

The results for the three open buy volume put-call ratio terciles are contained in Table 4. For $j = 2, 3,$ and $4,$ the middle put-call ratio tercile regression has the largest coefficient on the net demand variable. For $j = 1$ and $5,$ the coefficient on the net demand variable is second largest for the middle put-call ratio tercile and not much smaller than the largest one. Consequently, there is no evidence that the relationship between net option volume demand and future volatility is weaker when there is less directional information in the option volume. Indeed, it appears that the relationship is stronger when there is less directional information. We conclude that it is unlikely that our evidence that there is volatility information in the option volume is driven by directional information in the option volume.

4.2 Price impact and informational asymmetry

The previous subsection shows that non-market maker demand for volatility predicts the future volatility of underlying stocks. This fact was interpreted as evidence that investors bring volatility information to the option market. It is natural to explore the asset pricing consequences of investors bring volatility information to the option market, in particular, to see whether option prices are influenced by market makers "protecting" themselves from investors who possess private information about the future volatility of underlying stocks.

Table 5 reports the results from estimating equation (6) using pooled regressions. The *t*-statistics are computed from robust standard errors which are correct for cross-sectional correlation in the data. The coefficient on the volatility demand variable D is positive and highly significant which indicates that investor demand for volatility in the option market has a positive impact on option prices. This finding is consistent with the basic prediction of the Kyle model. Since the average level of implied volatility in our sample is about 0.60, the point estimate of 137.74 implies that a one standard deviation increase in volatility demand increases the difference between the implied volatility and realized volatility of a typical option by about 83 basis points.

Of more interest to us is the change in the price impact of volatility demand as information asymmetry increases leading up to EAD's. The coefficient on the interaction terms $D \times Ind(EAD+n)$ gives the incremental price impact of volatility demand due to the fact that it is day *n* relative to an EAD. In the five days leading up to the EAD (i.e., when $n = -5, -4, -3, -2,$ and -1), the marginal impact of volatility demand is positive with a coefficient ranging between 13 and 75. Furthermore, the coefficient estimates are monotonically increasing as the EAD is approached and the estimates for $n = -2$ and -1 are significant at conventional levels. These positive coefficient estimates indicate that when information asymmetry is greater in the days leading up to EADs, the price impact of a given quantity of volatility trading is greater. These results are consistent with market makers protecting themselves from a greater concentration of investors bringing volatility information to the option market just before EADs.

The indicator variables $Ind\left(EAD+n\right)$ are included to control for any overall changes in the spread between implied and realized volatility around EADs which are not related to volatility demand. The large coefficient estimates on these indicator variables on days $-1, 0,$ and $+1$ relative to the EAD indicate that the spread of implied volatility over realized volatility tends to be higher on these days. As was seen in Section 3, this increase in spread is driven by realized volatility dropping more than implied volatility when earnings are announced.

Table 6 re-runs the regressions when volatility demand is measured either from out-of-the-money (OTM), at-the-money (ATM), or in-the-money (ITM) options. We define the moneyness category of options in terms of the quantity $K/S-1$. OTM options are calls for which this quantity is greater than 0.1 or puts for which it is less than –0.1. ATM options are those for which this quantity has absolute value less then or equal to 0.1. ITM options are calls for which this quantity is less than –0.1 or puts for which it is greater than 0.1. In these regressions only options with 5 to 50 trading days to expiration and $\left|K/S-1\right|<0.20$ are considered.

The estimates in Table 6 show that the price impact from volatility demand is strongest for ATM options, less strong but still appreciable for OTM options, and much weaker for ITM options. These findings are not surprising, because ATM options have the greatest price sensitivity to volatility. Consequently, investors with volatility information are more likely to trade on it with ATM options, and market makers adjust option prices most aggressively in response to ATM volatility trading. These results provide an interesting contrast to the situation with directional information. Black (1975) hypothesizes and Easley, O'Hara and Srinivas (1998) show within a theoretical model that investors with directional information on underlying stocks will use more highly OTM contracts to trade in the option market. These predictions are confirmed empirically in Pan and Poteshman (2004).

When the concentration of informed investors is higher, market makers should be more concerned about taking the wrong side of "bad" trades and so should adjust option prices more aggressively in response to non-market maker demand for volatility. To test whether this is the case, we add to specification (6) terms which interact volatility demand with two proxies for the concentration of informed traders, *SIZE* and the *PIN* variable of Easley, Hvidkjaer, and O'Hara (2002). It is generally held that information flow is more efficient for large firms in which case firm size would be inversely related to the concentration of informed traded. Within the sequential trade model under which it is developed, *PIN* is a direct measure of the fraction of informed trading in the market.

Table 7 presents the results for specifications that include *SIZE* and *PIN*. The *PIN* measure is only available for NYSE and AMEX firms. In order to be able to assess the impact of including *SIZE* and *PIN*, we first re-run specification (6) on the subset of firms for which the *PIN* measure is available. The result is contained in the first column of Table 7, and the main features of the estimates are the same as before. The second regression reported in Table 7 includes a term which interacts volatility demand with $\ln(SIZE)$. This term gets a highly significant coefficient estimate of –29.53 which indicates that for a typical underlying stock (which has implied volatility of around 0.60) each unit increase in $\ln(SIZE)$ decreases the price impact of one standard deviation of volatility demand by about $18(\approx 0.6 \times 29.53)$ basis points. This finding is consistent with the view that larger stocks have a lower concentration of informed trades and that market makers, therefore, adjust prices less aggressively in response to volatility demand.

The third regression reported in Table 7 includes a term which interacts demand volatility with the *PIN* variable. The coefficient estimate for this term is 477 which is also highly significant. The fact that this coefficient is positive indicates that in accordance with the Kyle model, market makers adjust prices more aggressively in response to volatility demand when there is higher concentration of informed trading. The *PIN* is defined so that it can range from 0 (no informed trades) to 1 (all informed trades). This suggests that the average price impact of one standard deviation of demand volatility for a typical underlying stock is about $286\left(\approx 0.6 \times 477\right)$ basis points greater for high than low *PIN* stocks. It is important to recognize, however, that this conclusion involves an extrapolation, because no stock in our sample has *PIN* as small as 0 or as large as 1. In fact, across the daily cross-sections the average minimum *PIN* value is 0.05 and the average maximum *PIN* value is 0.28 (while the average median is 0.13). This implies that moving from underlying stocks with low to high *PIN*, the additional gain in price impact from a one standard deviation shock to volatility demand is on the order of 66 basis points.

5. Conclusion

Options play several important economic roles including that of providing a venue for investors to bring information to the financial markets. Investors can trade on directional information in either the stock or the option market, and a number of papers have investigated the use of the option markets to incorporate directional information about firms. The option market is uniquely suited for the incorporation of volatility information into financial markets, yet there is little research on the issues of whether options are used for this purpose, and, if so, on the asset pricing implications.

This paper provides evidence that investors bring volatility information to the option market by showing that non-market maker net volatility demand in the option market is positively related to subsequent realized volatility by underlying stocks. This finding demonstrates that option volume is informative about future volatility and is also consistent with investors bringing volatility information to the option market. We also show that the non-market maker net volatility demand from transactions that open new option positions is a stronger predictor of future volatility than the non-market maker net volatility demand which closes existing option positions. This result provides confirmation that the informativeness of the option volume for future volatility derives from investors bringing volatility information to the option market.

We also find that net volatility demand impacts the prices of options and that the impact per unit of net volatility demand increases in the days leading up to earnings announcements when informational asymmetry increases. This finding is consistent with option market makers changing prices in order to protect themselves from investors with volatility information and with market makers becoming more concerned with protecting themselves at times when information asymmetry is especially high.

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Table 1: Summary Statistics

This table reports summary statistics from the beginning of 1990 through the end of 2001 for the variables used in the paper's tests. Implied volatility is the average implied volatility of the selected straddle's call and put, and realized volatility is the realized stock volatility over the remaining life of the selected straddle. IV change is calculated from the implied volatility of the straddle at date t minus the implied volatility of same straddle at date $t-1$. (dIV – dRV)/IV is the difference between IV change and RV change divided by previous day's implied volatility of the same straddle. Stock (H-L)/S is the difference of an underlying stocks intraday high and low divided by the previous day's closing stock price.

	mean	std	auto	skew	kurt	min	max
Implied volatility (IV) (bps)	6445.64	2962.01	0.84	0.85	3.41	279.24	17999.50
Realized volatility (RV) (bps)	6156.09	3911.39	0.74	1.94	9.93	210.51	51995.25
IV change (dIV) (bps)	-2.44	441.70	-0.03	-0.36	33.46	-12796.00	7781.50
RV change (dRV) (bps)	-56.68	606.33	0.00	-4.92	46.33	-13160.67	2790.56
dIV – dRV (bps)	54.23	747.61	-0.02	2.84	26.51	-12913.36	12913.17
(dIV - dRV)/IV0 (bps)	75.53	1226.11	-0.02	-1.38	87.84	-53750.79	37642.30
Straddle return (bps)	-446.37	931.00	-0.01	-0.35	12.17	-8719.12	10416.54
Stock |return| (bps)	329.97	355.59	0.08	2.70	15.08	0.00	5619.69
Stock (H-L)/S (unitless)	520.21	410.02	0.37	2.49	14.61	6.25	6600.98
Volatility demand (contracts)	-27.53	643.91	0.04	0.58	566.33	-49664.00	42982.00
Net bought call volume (contracts)	-31.21	631.13	0.08	0.81	334.30	-41194.00	38484.00
Net bought put volume (contracts)	-23.86	623.35	0.10	1.58	269.03	-26134.00	37622.00
Net bought open volume (contracts)	56.48	741.62	0.10	10.00	709.32	-58904.00	59904.00
Net bought open call volume (contracts)	50.83	660.84	0.08	9.74	402.74	-29796.00	46008.00
Net bought open put volume (contracts)	62.14	602.51	0.10	5.50	264.04	-29800.00	37281.00
Stock daily volume (1,000,000s shares)	2.23	5.22	0.47	10.77	214.83	0.001	318.76

Table 2: Correlation Coefficients

This table reports the correlation coefficients for a number of variables over the January 1990 through December 2001 time period. Implied volatility is the average implied volatility of the selected straddle call and put, and realized volatility is the realized stock volatility over the remaining life of the selected straddle. IV change is calculated from the implied volatility of the straddle at date *t* minus the implied volatility of same straddle at date $t-1$. (dIV – dRV)/IV is the difference between IV change and RV change divided by the previous day's implied volatility of the same straddle.

	IV	RV	dIV	dRV	dIV - dRV	(dIV – dRV)/IV	Strad ret	Stock |ret|	Volatility Demand	Net bought open volume
RV	0.43									
dIV	0.14	0.07								
dRV	-0.05	0.24	0.01							
dIV - dRV	0.12	-0.15	0.60	-0.79						
(dIV – dRV)/IV	0.10	-0.09	0.60	-0.54	0.80					
Straddle ret	0.00	-0.02	0.36	0.13	0.11	0.16				
Stock |ret|	0.25	0.17	0.04	-0.80	0.66	0.45	-0.17			
Volatility demand	0.00	0.04	0.25	0.05	0.11	0.11	0.08	-0.02		
Net bought open volume	0.03	0.05	0.20	-0.03	0.14	0.13	0.06	0.05	0.72	
Stock volume	0.32	0.16	0.01	-0.32	0.26	0.19	-0.06	0.40	-0.04	0.08

Table 3: The Information in Option Demand for Volatility for Future Volatility of the Underlying Stock

This table reports estimates from pooled regressions over 1990-2001. The dependent variable, $OneDayRV_{i,t}$, is a proxy for the realized volatility on stock i on trade day t. The proxy is 10,000 times the difference between the stock's intraday high and low price divided by the previous day's closing stock price. The net demand variable, D, is the demand for volatility in the option market for underlying stock i on trade day t-j. In the three panels it is computed either from both open and close option volume or only open or close option volume. The Ind variable is 1 if trade day t is an earnings announcement day for stock i and otherwise is 0. The $stkVolume$ variable is the number of shares of stock i that trade on day t-j. The five panels contain the results for $j = 1,...,5$. The square brackets contain t-statistics computed from robust standard errors which correct for cross-sectional correlation in the data.

j	Constant	$D_{i,t-j}$	$D_{i,t-j}\times Ind_{i,t}$	$OneDayRV_{i,t}$	$OneDayRV_{i,t}$ $\times Ind_{i,t}$	$\ln(stkVolume_{i,t-j})$	$\ln(stkVolume_{i,t-j})$ $\times Ind_{i,t}$
Panel A: Net Demand Computed from Open and Close Option Volume							
1	-0.098	11.68	32.18	81.14	-6.24	11.96	0.05
	[-0.04]	[16.63]	[8.84]	[26.63]	[-1.08]	[8.00]	[0.01]
2	-0.032	7.25	11.24	82.47	-2.17	17.17	-4.51
	[-0.01]	[12.18]	[2.96]	[31.15]	[-0.39]	[17.80]	[-0.88]
3	-0.035	6.76	10.96	84.59	-1.96	14.05	-9.99
	[-0.01]	[10.02]	[2.35]	[30.88]	[-0.35]	[14.40]	[-1.83]
4	-0.025	5.93	17.61	84.70	-1.32	12.76	5.89
	[-0.01]	[9.65]	[3.84]	[30.30]	[-0.23]	[12.34	[1.07]
5	-0.019	5.18	12.67	85.16	1.37	10.18	1.24
	[-0.01]	[8.95]	[2.72]	[30.69]	[0.24]	[8.41]	[0.24]
Panel B: Net Demand Computed from Open Option Volume							
1	-0.102	9.61	28.82	80.88	-7.64	10.82	-4.80
	[-0.04]	[15.29]	[8.31]	[26.42]	[-1.30]	[7.15]	[-1.08]
2	-0.031	5.77	11.42	82.54	-2.12	16.33	-5.69
	[-0.01]	[9.56]	[2.91]	[31.10]	[-0.38]	[16.81]	[-1.08]
3	-0.045	6.13	17.68	84.63	-2.02	13.16	-11.84
	[-0.02]	[9.00]	[3.01]	[30.85]	[-0.35]	[13.49]	[-2.12]
4	-0.022	4.98	17.57	84.74	-1.31	12.04	3.79
	[-0.01]	[7.34]	[3.66]	[30.32]	[-0.23]	[11.57]	[0.70]
5	-0.021	4.22	16.03	85.20	1.24	9.57	-0.48
	[-0.01]	[6.46]	[3.32]	[30.72]	[0.22]	[7.77]	[-0.09]
Panel C: Net Demand Computed from Close Option Volume							
1	0.020	3.83	7.18	81.96	-4.96	12.28	2.56
	[0.01]	[5.76]	[1.93]	[26.50]	[-0.85]	[8.37]	[0.56]
2	-0.002	2.58	-0.77	82.85	-1.13	17.64	-4.72
	[0.00]	[4.24]	[-0.15]	[31.16	[-0.21]	[17.64]	[-0.92]
3	-0.008	1.35	-7.93	84.84	-1.16	14.31	-11.09
	[0.00]	[2.18]	[-1.36]	[30.86]	[-0.20]	[14.23]	[-2.00]
4	0.005	1.88	4.11	84.89	-0.89	13.14	6.56
	[0.00]	[3.20]	[0.79]	[30.36]	[-0.15]	[12.32]	[1.15]
5	-0.005	1.99	-5.26	85.29	1.72	10.59	0.04
	[0.00]	[3.32]	[-1.06]	[30.77]	[0.30]	[8.47]	[0.01]

Table 4: The Information in Option Demand for Volatility for Future Volatility of the Underlying Stock Controlling for Directional Information in Option Volume

This table reports estimates from pooled regressions over 1990-2001. The dependent variable, $OneDayRV_{i,t}$, is a proxy for the realized volatility on stock *i* on trade day *t*. The proxy is 10,000 times the difference between the stock's intraday high and low price divided by the stock's price closing price on the preceding day. The D variable is the demand for volatility in the option market for underlying stock *i* on trade day *t-j*. The *Ind* variable is 1 if trade day *t* is an earnings announcement day for stock *i* and otherwise is 0. The *stkVolume* variable is the number of shares of stock *i* that trade on day *t-j*. The three panels contain the results from running the regressions on underlying stocks in the lowest (1), middle (2), and highest (3) terciles of open buy volume put-call ratio. The square brackets contain *t*-statistics computed from robust standard errors which correct for cross-sectional correlation in the data.

j	Constant	$D_{i,t-j}$	$D_{i,t-j}\times Ind_{i,t}$	$OneDayRV_{i,t}$	$OneDayRV_{i,t} \times Ind_{i,t}$	$\ln(stkVolume_{i,t-j})$	$\ln(stkVolume_{i,t-j}) \times Ind_{i,t}$
			Panel A: Low PC Tercile				
1	-0.02	8.48	26.30	61.07	-15.92	9.81	-7.53
	[-0.01]	[10.82]	[3.36]	[30.44]	[-1.91]	[10.01]	[-0.87]
2	-0.08	5.58	22.25	69.66	3.78	15.22	-12.90
	[-0.04]	[6.50]	[2.74]	[37.53]	[0.40]	[15.40]	[-1.34]
3	-0.08	5.13	26.77	72.36	0.59	11.07	-10.70
	[-0.04]	[5.05]	[3.12]	[35.59]	[0.07]	[10.40]	[-1.37]
4	0.00	4.09	3.35	72.38	-1.10	10.36	-2.00
	[0.00]	[4.43]	[0.43]	[34.54]	[-0.11]	[10.38]	[-0.20]
5	-0.03]	2.46	16.70	73.94	0.86	8.09	-1.59
	[-0.01]	[2.76]	[1.88]	[35.99]	[0.10]	[7.70]	[-0.17]
			Panel B: Middle PC Tercile				
1	-0.08	11.77	28.15	92.53	-4.44	13.52	-9.82
	[-0.03]	[10.71]	[4.20]	[23.50]	[-0.51]	[7.12]	[-1.37]
2	-0.04	8.25	9.08	92.20	4.65	18.19	3.61
	[-0.01]	[8.76]	[1.24]	[27.01]	[0.53]	[15.47]	[0.44]
3	-0.01	7.66	3.04	93.59	-1.13	15.54	-2.21
	[0.00]	[7.43]	[0.40]	[28.06]	[-0.14]	[13.02]	[-0.26]
4	-0.09	6.65	23.41	94.49	11.16	15.18	9.96
	[-0.03]	[7.44]	[2.78]	[27.19]	[1.31]	[11.25]	[1.17]
5	-0.05	4.25	17.30	93.99	5.43	11.62	-3.31
	[-0.01]	[4.84]	[1.92]	[29.49]	[0.64]	[7.29]	[-0.36]
			Panel C: High PC Tercile				
1	-0.09	12.51	28.61	78.19	-2.35	10.51	-1.83
	[-0.04]	[14.55]	[5.63]	[26.29]	[-0.29]	[6.46]	[-0.26]
2	-0.04	6.70	5.66	80.24	-1.43	15.12	-15.69
	[-0.02]	[8.72]	[0.96]	[29.61]	[-0.20]	[12.85]	[-2.41]
3	-0.06	6.42	11.60	82.71	3.61	13.16	-13.91
	[-0.02]	[8.04]	[1.41]	[28.76]	[0.46]	[11.30]	[-1.93]
4	-0.04	6.23	15.15	82.49	3.70	11.34	2.89
	[-0.01]	[7.63]	[2.20]	[29.15	[0.44]	[9.74]	[0.37]
5	0.00	5.89	10.40	84.28	1.01	9.18	12.41
	[0.00]	[7.92]	[1.53]	[26.78]	[0.13]	[7.00]	[1.73]

Table 5: Price Impact of Volatility Demand

This table reports estimates from pooled regressions over 1990-2001. The dependent variable is 10,000 times the difference in the daily change in implied volatility and the daily change in the realized volatility divided by the level of the implied volatility for underlying stock *i* on trade date *t*. The D variable is the demand for volatility in the option market for underlying stock *i* on trade day *t*. The demand is computed from options with maturities between 5 and 50 trading days and $|S/K-1|<0.20$. The $Ind(EAD-n)$ variable is 1 if trade day $t+n$ is an earnings announcement day for stock *i* and otherwise is 0. The square brackets contain *t*-statistics computed from robust standard errors which correct for cross-sectional correlation in the data.

Intercept	-14.23	[-2.25]
D	137.74	[30.10]
$D \times Ind(EAD-5)$	13.28	[0.53]
$D \times Ind(EAD-4)$	19.66	[0.93]
$D \times Ind(EAD-3)$	39.16	[1.27]
$D \times Ind(EAD-2)$	67.81	[2.67]
$D \times Ind(EAD-1)$	75.47	[3.59]
$D \times Ind(EAD-0)$	-41.57	[-1.84]
$D \times Ind(EAD+1)$	-47.65	[-1.79]
$D \times Ind(EAD+2)$	-9.11	[-0.45]
$D \times Ind(EAD+3)$	-8.91	[-0.44]
$D \times Ind(EAD+4)$	-21.60	[-1.14]
$D \times Ind(EAD+5)$	-28.22	[-1.00]
$Ind(EAD-5)$	1.12	[0.06]
$Ind(EAD-4)$	16.13	[0.78]
$Ind(EAD-3)$	20.98	[1.12]
$Ind(EAD-2)$	47.46	[2.12]
$Ind(EAD-1)$	131.31	[6.42]
$Ind(EAD-0)$	325.65	[13.22]
$Ind(EAD+1)$	250.89	[9.28]
$Ind(EAD+2)$	27.32	[1.23]
$Ind(EAD+3)$	-49.33	[-2.47]
$Ind(EAD+4)$	-42.40	[-2.01]
$Ind(EAD+5)$	-22.13	[-1.07]

Table 6: Price Impact of Volatility Demand by Moneyness

This table reports estimates from pooled regressions over 1990-2001. The dependent variable is 10,000 times the difference in the daily change in implied volatility and the daily change in the realized volatility divided by the level of the implied volatility for underlying stock *i* on trade date *t*. The D variable is the demand for volatility in the option market for underlying stock *i* on trade day *t*. The demand is computed from options with maturities between 5 and 50 trading days, $|S/K-1|<0.20,$ and the indicated further restrictions on moneyness. The $Ind\left(EAD-n\right)$ variable is 1 if trade day $t+n$ is an earnings announcement day for stock *i* and otherwise is 0. The square brackets contain *t*-statistics computed from robust standard errors which correct for cross-sectional correlation in the data.

Variable	OTM: $K/S-1>0.1$ (Calls) $K/S-1<-0.1$ (Puts)		ATM: $\lvert K/S-1\rvert \le 0.1$		ITM: $K/S-1<-0.1$ (Calls) $K/S-1>0.1$ (Puts)	
Intercept	-12.68	[-1.54]	-13.28	[-2.03]	-14.79	[-1.54]
D	120.01	[20.97]	137.30	[30.46]	-28.47	[-3.61]
$D\times Ind\left(EAD-5\right)$	59.35	[1.03]	5.16	[0.17]	-44.12	[-0.84]
$D\times Ind\left(EAD-4\right)$	41.92	[1.57]	-8.87	[-0.40]	68.63	[1.94]
$D\times Ind\left(EAD-3\right)$	15.58	[0.45]	74.90	[2.01]	10.51	[0.29]
$D\times Ind\left(EAD-2\right)$	47.71	[1.51]	75.32	[3.09]	-70.65	[-1.38]
$D\times Ind\left(EAD-1\right)$	36.95	[0.83]	53.53	[2.67]	119.80	[2.04]
$D\times Ind\left(EAD-0\right)$	57.82	[1.68]	-59.85	[-2.28]	-32.60	[-0.64]
$D\times Ind\left(EAD+1\right)$	119.60	[3.15]	-32.98	[-1.22]	-147.67	[-2.87]
$D\times Ind\left(EAD+2\right)$	33.13	[1.03]	-6.18	[-0.29]	-102.70	[-2.23]
$D\times Ind\left(EAD+3\right)$	2.24	[0.10]	-2.31	[-0.10]	33.48	[0.75]
$D\times Ind\left(EAD+4\right)$	25.12	[0.55]	-17.38	[-0.86]	-53.97	[-1.10]
$D\times Ind\left(EAD+5\right)$	12.86	[0.32]	-45.00	[-1.65]	-91.47	[-2.14]
$Ind\left(EAD-5\right)$	68.44	[2.40]	17.62	[0.85]	88.14	[2.05]
$Ind\left(EAD-4\right)$	0.69	[0.03]	10.38	[0.48]	-19.53	[-0.51]
$Ind\left(EAD-3\right)$	10.26	[0.38]	20.58	[1.02]	32.66	[0.85]
$Ind\left(EAD-2\right)$	64.72	[2.04]	49.44	[2.12]	94.45	[1.92]
$Ind\left(EAD-1\right)$	190.46	[6.90]	145.24	[6.50]	206.58	[5.47]
$Ind\left(EAD-0\right)$	339.10	[10.39]	325.01	[12.41]	392.99	[8.61]
$Ind\left(EAD+1\right)$	225.86	[6.12]	223.97	[7.97]	138.94	[3.06]
$Ind\left(EAD+2\right)$	-39.00	[-1.28]	-3.20	[-0.15]	-92.20	[-2.54]
$Ind\left(EAD+3\right)$	-95.78	[-4.19]	-61.73	[-2.99]	-118.74	[-3.95]
$Ind\left(EAD+4\right)$	-54.26	[-2.03]	-53.13	[-2.30]	-46.27	[-1.20]
$Ind\left(EAD+5\right)$	-71.57	[-2.77]	-21.83	[-0.96]	-63.85	[-1.78]

Table 7: Price Impact of Volatility Demand Conditioning on SIZE and PIN

This table reports estimates from pooled regressions over 1990-2001. The dependent variable is 10,000 times the difference in the daily change in implied volatility and the daily change in the realized volatility divided by the level of the implied volatility for underlying stock *i* on trade date *t*. The D variable is the demand for volatility in the option market for underlying stock *i* on trade day *t*. The demand is computed from options with maturities between 5 and 50 trading days and $\left|S/K-1\right|<0.20$. The *SIZE* variable is firm *i*'s beginning of month dollar market capitalization divided by 1000. The *PIN* variable is Easley, Hvidkjaer, and O'Hara's (2002) measure of the probability that a given trade on stock *i* is information based. The $Ind\left(EAD-n\right)$ variable is 1 if trade day $t+n$ is an earnings announcement day for stock *i* and otherwise is 0. The square brackets contain *t*-statistics computed from robust standard errors which correct for cross-sectional correlation in the data.

Intercept	-13.48	[-2.05]	-13.27	[-2.02]	-13.02	[-1.97]
D	127.16	[24.36]	388.36	[14.22]	70.76	[4.87]
$D\times\ln\left(SIZE\right)$			-29.53	[-9.81]		
$D\times PIN$					477.28	[4.15]
$D\times Ind\left(EAD-5\right)$	10.52	[0.34]	8.49	[0.27]	9.40	[0.30]
$D\times Ind\left(EAD-4\right)$	13.98	[0.48]	14.89	[0.50]	17.07	[0.58]
$D\times Ind\left(EAD-3\right)$	20.43	[0.67]	22.77	[0.75]	22.75	[0.74]
$D\times Ind\left(EAD-2\right)$	137.91	[3.58]	136.65	[3.55]	136.69	[3.55]
$D\times Ind\left(EAD-1\right)$	69.44	[2.42]	69.70	[2.44]	69.16	[2.42]
$D\times Ind\left(EAD-0\right)$	13.57	[0.42]	9.92	[0.31]	11.14	[0.34]
$D\times Ind\left(EAD+1\right)$	-38.82	[-1.16]	-42.73	[-1.28]	-39.49	[-1.17]
$D\times Ind\left(EAD+2\right)$	19.85	[0.77]	16.27	[0.63]	14.43	[0.59]
$D\times Ind\left(EAD+3\right)$	27.34	[0.87]	25.35	[0.83]	25.09	[0.80]
$D\times Ind\left(EAD+4\right)$	8.01	[0.26]	6.41	[0.21]	8.98	[0.29]
$D\times Ind\left(EAD+5\right)$	-48.19	[-1.21]	-49.01	[-1.23]	-44.21	[-1.10]
$Ind\left(EAD-5\right)$	-12.60	[-0.54]	-14.50	[-0.62]	-13.39	[-0.57]
$Ind\left(EAD-4\right)$	41.09	[1.35]	39.88	[1.32]	41.04	[1.36]
$Ind\left(EAD-3\right)$	36.33	[1.36]	35.52	[1.33]	35.87	[1.34]
$Ind\left(EAD-2\right)$	42.18	[1.64]	39.84	[1.55]	41.14	[1.60]
$Ind\left(EAD-1\right)$	127.84	[4.79]	126.41	[4.74]	127.90	[4.79]
$Ind\left(EAD-0\right)$	325.97	[9.06]	324.53	[9.02]	327.41	[9.07]
$Ind\left(EAD+1\right)$	159.13	[4.84]	160.82	[4.88]	157.19	[4.77]
$Ind\left(EAD+2\right)$	48.50	[1.91]	47.34	[1.87]	50.22	[1.98]
$Ind\left(EAD+3\right)$	-47.53	[-1.53]	-48.51	[-1.56]	-47.77	[-1.54]
$Ind\left(EAD+4\right)$	-36.80	[-1.15]	-38.35	[-1.19]	-37.06	[-1.15]
$Ind\left(EAD+5\right)$	5.69	[0.21]	5.33	[0.20]	6.57	[0.24]

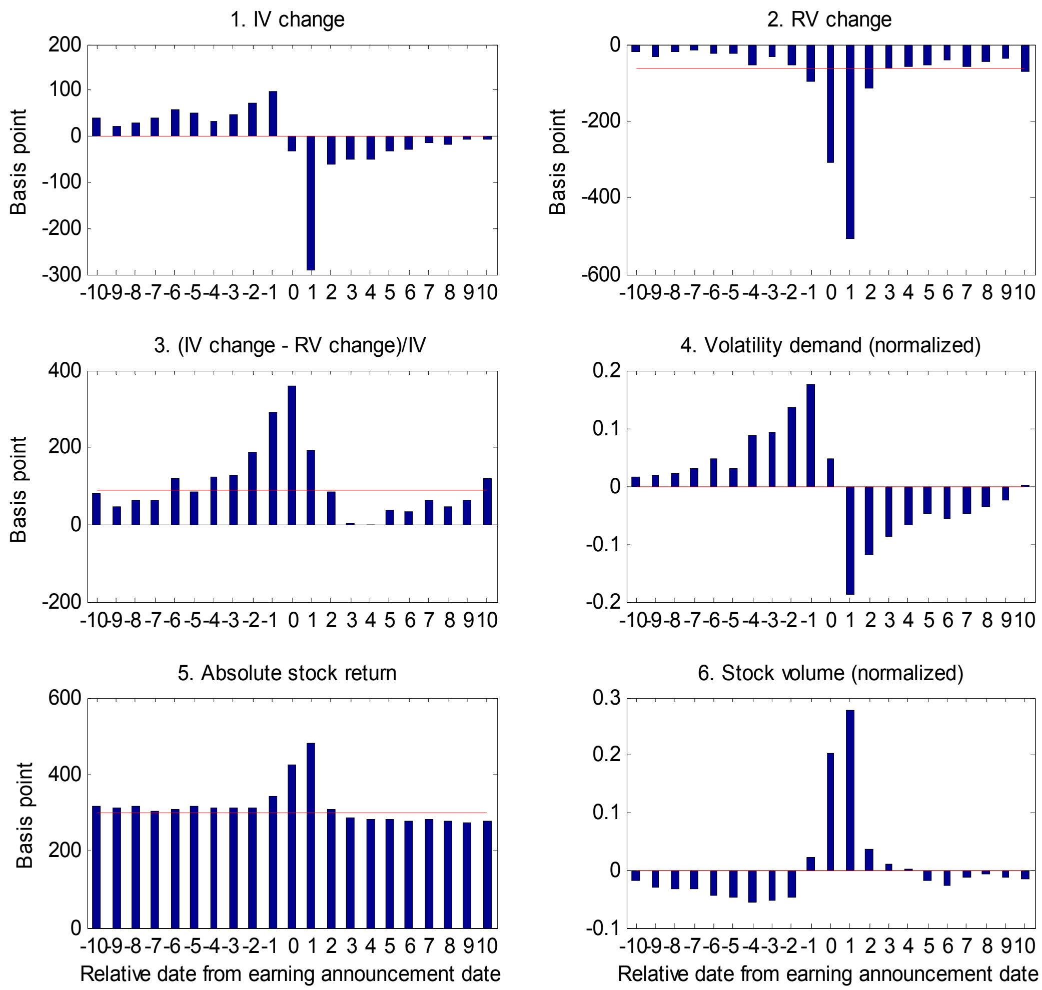

Figure 1. Average value of variables various number of trade days relative to earnings announcement dates. This figure reports the average value of variables at various numbers of trade days relative to earnings announcement dates. The horizontal lines correspond to the average value of the variable across the entire sample. IV change is the implied volatility of a short maturity approximately at-the-money straddle at date t minus the implied volatility of the same straddle at date $t-1$. RV change is the date t minus the date $t-1$ realized volatility for the same straddle. (dIV – dRV)/IV is the difference between IV change and RV change divided by the previous day's implied volatility for the same straddle. Volatility demand is the normalized net volatility demand on the straddle's underlying stock.