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Volatility Information Trading in the Option Market

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ABSTRACT

This paper investigates informed trading on stock volatility in the option market. We construct non-market maker net demand for volatility from the trading volume of individual equity options and find that this demand is informative about the future realized volatility of underlying stocks. We also find that the impact of volatility demand on option prices is positive. More importantly, the price impact increases by 40% as informational asymmetry about stock volatility intensifies in the days leading up to earnings announcements and diminishes to its normal level soon after the volatility uncertainty is resolved.

THE LAST SEVERAL DECADES have witnessed astonishing growth in the market for derivatives. The market's current size of $200 trillion is more than 100 times greater than 30 years ago (Stulz (2004)). Accompanying this impressive growth in size has been an equally impressive growth in variety: The derivatives market now covers a broad spectrum of risk, including equity risk, interest rate risk, weather risk, and, most recently, credit risk and inflation risk. This phenomenal growth in size and breadth underscores the role of derivatives in financial markets and their economic value. While financial theory has traditionally emphasized the spanning properties of derivatives and their consequent ability to improve 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)).

We contribute to the body of knowledge on the economic value of derivatives by investigating the role of options as a mechanism for trading on information about future 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. Unlike traders with

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directional information about underlying stock prices who can trade in either the stock or option markets, traders with volatility information can only use nonlinear securities such as options. Moreover, while the question of whether traders use options to trade on directional information has been examined in some detail (Stephan and Whaley (1990), Amin and Lee (1997), Easley, O'Hara, and Srinivas (1998), Chan, Chung, and Fong (2002), Chakravarty, Gulen, and Mayhew (2004), Cao, Chen, and Griffin (2005), and Pan and Poteshman (2006)), the analogous question about volatility information trading has not been systematically addressed in the literature.[1] Since volatility plays such a central role in both the pricing of options and the reasons for trading options, a better understanding of volatility information trading is clearly important.

Our empirical investigation takes advantage of a unique data set from the Chicago Board Options Exchange (CBOE) that records purchases and sales of put and call options by non-market makers over the 1990 to 2001 period. For each underlying stock, we construct daily non-market maker net demand for volatility. Motivated by theoretical models of private information trading, particularly those of Kyle (1985) and Back's (1993) extension of it to a setting that include options, we pursue two strands of empirical investigation to examine the presence of volatility information trading in the option market. First, we investigate the extent to which the volatility demand extracted from the option market predicts the future volatility realized by underlying stocks. Second, we examine the price impact of volatility demand, focusing especially on the time variation of the price impact leading up to earnings announcements when the level of informational asymmetry is high. Both of these strands yield evidence in support of volatility information trading in the option market.

Our first main finding is that option market demand for volatility predicts the future realized volatility of underlying stocks even after controlling for option implied volatility and a number of other variables. The predictability lasts at least 1 week into the future and is robust to different measures of realized volatility and controls for directional information in the option volume. A natural interpretation of the evidence that option volume is informative about future volatility is that investors trade on volatility information in the option market and the information is subsequently reflected in the underlying stocks.

[1] The mass media, however, often attributes option market activity to volatility trading. For example, on October 5, 2006, the *Wall Street Journal* reported heavy trading of McDonald's options (Hodi (2006f)): "Nearly 100,000 calls and 94,000 put options changed hands, many of them simultaneously, in a position called a straddle. A straddle involves buying a put and a call at the same strike price, and profits from a large move in the stock in either direction." More interestingly, a large fraction of these straddles targeted the November contracts. The catalyst for the trading? "The Company is due to report September sales on Oct. 12. McDonald's tends to preview quarterly earnings during such reports. The company is expected to report detailed earnings for the third-quarter later this month" (Hadi (2006f)). For further examples, see Hadi (2006a–2006e). Lakonishok, Lee, Pearson, and Poteshman (2007) provide evidence that only a small percentage of the option trading of customers of a discount brokerge house could be part of volatility trades such as straddles or strangles. Pearson, Poteshman, and White (2007) show that option trading impacts the volatility of underlying stocks.

This interpretation is corroborated by two additional results. First, we find that the non-market maker net demand for volatility constructed from open option volume (trades in which non-market makers open brand new option positions) has stronger predictability in both magnitude and statistical significance than that constructed from close option volume (trades in which non-market makers close existing option positions). While both open and close trades can be informationally motivated, the informational content of 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 of the net demand constructed from open volume is therefore consistent with the predictability we identify having its economic source in volatility information trading in the option market.[2] Second, we find that the net demand for volatility constructed from option volume that could have been part of straddle trades is a stronger predictor of future volatility than net demand for volatility constructed from option volume that could not have been part of straddle trades. Since straddles are the leading strategy for trading on volatility, the stronger predictability of the volume with the higher concentration of straddle trading is also consistent with the predictability we identify originating from informed volatility trading in the option market.

Our second main finding is that volatility demand has a positive and time-varying price impact that increases on days leading up to earnings announcements. In standard information trading models such as that in Kyle (1985), the presence of informational asymmetry induces the market maker to adjust price in response to demand, resulting in a positive relation between equilibrium price and demand. Our empirical analysis shows that the net demand for volatility indeed positively impacts option prices.

Although the finding of a positive price impact confirms a prediction of the hypothesis that option investors trade on private volatility information, it could also be produced by demand pressure that is unrelated to informational asymmetry. We offer two additional results to assess whether the positive price impact is produced by demand pressure alone. In both analyses, we take advantage of the fact that unlike pure demand pressure, the price impact caused by informational asymmetry depends in an important way on the level of informational asymmetry. We first employ earnings announcements to exploit time variation in informational asymmetry. Prescheduled earnings announcements are exogenous information events. Thus, in the period leading up to earnings 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

[2] An alternative explanation for this result is that closing trades are more likely to be in-the-money or out-of-the-money, both of which are less sensitive to volatility. To check whether this is the case, we compared the relative predictability within each category of moneyness and found that the predictability from opening option transactions dominates that from closing option transactions regardless of the moneyness category.

option market makers.[3] Our results show that the price impact per unit of non-market maker net demand for volatility increases as informational asymmetry increases in the week leading up to EADs. By the day before EADs, the price impact per unit of volatility demand increases to 40% above its normal level. 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 is consistent with market makers protecting themselves from option market trades motivated by volatility information.[4]

To further address the alternative hypothesis of demand pressure, we make use of the fact that volume that opens and closes option positions is associated with different levels of informational asymmetry. For example, in our predictive analysis, we find that the non-market maker net demand for volatility constructed from open option volume has stronger predictability than that from close option volume, indicating a higher informational content for the open volume. Similarly, Pan and Poteshman (2006) show that open volume contains more information than close volume about the future direction of underlying stock prices. If the market makers possess any ability to distinguish open trades from close trades, they will react more to open volume because of its greater informational content.[5] This additional price impact is unrelated to pure demand pressure and can be attributed to informational asymmetry. Our analysis indicates that open volume does indeed have a greater price impact.

Our paper relates to several strands of the empirical option literature. First, our predictive analysis is related to the literature that examines the informational content of option-implied volatility for future realized volatility.[6] A common finding in these papers is that the implied volatility subsumes other publicly available information, including the past-realized volatility (e.g., see Christensen and Prabhala (1998)). The reason that implied volatility provides better predictions may be that information about future volatility is impounded

[3] 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.

[4] It is also interesting to note that the predictive power of net volatility demand approximately doubles on the day before EADs compared to the average level of 1-day ahead predictability. This result is consistent with the hypothesis that volatility demand contains more information before EADs.

[5] Although the market makers do not directly observe in real time whether trades open or close option positions, at the end of the day they can infer the breakdown of open versus close trades during the day from changes in open interest. It seems likely that they would develop some real-time ability to assess the probability that trades coming into the market are opening or closing positions.

[6] See, for example, Latane and Rendleman (1976), Canina and Figlewski (1993), Christensen and Prabhala (1998), Day and Lewis (1992), Jorion (1995), Lamoureux and Lastrapes (1993), Poteshman (2000), Ederington and Guan (2002), and Chernov (2002). In a similar vein, Ederington and Lee (1996) investigate the impact of news on option implied volatility.

into option prices through the trading process. By using quantity information in addition to price information, our predictive analysis complements this literature by examining the process of information incorporation at the level of option trading. In particular, we find that even though the non-market maker net demand for volatility is observable by market makers, it provides information about future volatility beyond what is contained in option-implied volatility.[7]

Our findings are also related to a number of studies that examine stock option prices and trading volume in the time surrounding earnings announcements (Patell and Wolfson (1979, 1981) and Whaley and Cheung (1982)). For example, Amin and Lee (1997) investigate abnormal trading volume in the option market around the announcement of earnings news and provide evidence of directional information trading in the option market. Donders, Kouwenberg, and Vorst (2000) and Dubinsky and Johannes (2005) document the impact of earnings announcements on equity option prices and find that implied volatility increases before EADs and drops afterward, as suggested in Ederington and Lee (1996) for prescheduled events. Dubinsky and Johannes (2005) also develop an option pricing model to incorporate jumps on EADs and find that firms with high option-implied estimates of earnings uncertainty subsequently have volatile stock returns on EADs. This long line of research attests to the importance of earnings announcements as informational events in the equity option market. Our analysis adds to this body of literature by addressing time variation in the level of informational asymmetry surrounding these announcements. In particular, we provide empirical evidence to link time variation in informational asymmetry directly to time variation in the price impact in the equity option market.

Finally, our findings on the option price impact of volatility demand are related to two recent papers that investigate the relationship between the demand for options and the prices of options. Bollen and Whaley (2004) show that option-implied volatilities are positively related to the net buying pressure for options, consistent with our finding of a positive price impact. They also find that approximately 20% of the price impact is reversed the next day, suggesting that price pressure is one component of the positive price impact. By contrast, the main objective of the second strand of our empirical work is to determine whether there is a component of price impact that relates to volatility information trading. We do so by investigating the connection between time variation in price impact and time variation in informational asymmetry as well as the differential price impact of open and close option volume. Our empirical results are also related to the findings of Gârleanu, Pedersen, and Poteshman (2006), who develop a theoretical model linking the level of aggregate demand to the level of option prices and provide empirical support for their model's predictions. The Gârleanu et al. (2006) paper is agnostic about the source of option demand. We provide evidence that the demand comes in part from investors

[7] A caveat here is that the papers in this literature typically predict the realized volatility over the life of the option from which volatility is implied while we predict volatility over only one future trading day.

with volatility information and that this component of demand impacts option prices.

The rest of the paper is organized as follows. Section I develops our empirical specifications. Section II details the data, and Section III presents the results. Finally, Section IV concludes.

I. Empirical Specification

A. Information in Option Volume for Future Stock Volatility

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 non-market maker net demand for volatility 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. Both call and put options have positive "vega" (exposure to volatility), so we treat buy volume for both call and put options as positive demand for volatility and sell volume as negative demand for volatility. Since options of varying strike prices and maturities have differing sensitivities to changes in volatility, we weight the demand for each contract by the return to the option per unit change in volatility. Specifically, for each stock i on day t, the daily demand for volatility is measured by

$$
\begin{aligned}
D_{i,t}^{\sigma} \equiv & \sum_K \sum_T \frac{\partial \ln C_{i,t}^{K,T}}{\partial \sigma_{i,t}} \left(BuyCall_{i,t}^{K,T} - SellCall_{i,t}^{K,T} \right) \\
& + \sum_K \sum_T \frac{\partial \ln P_{i,t}^{K,T}}{\partial \sigma_{i,t}} \left(BuyPut_{i,t}^{K,T} - SellPut_{i,t}^{K,T} \right), \qquad (1)
\end{aligned}
$$

where $C_{i,t}^{K,T}$ is the price at time t of the call on underlying stock i with strike price K and maturity T; $P_{i,t}^{K,T}$ is the price for the similar put; $\sigma_{i,t}$ is the volatility of underlying stock i at time t; $BuyCall_{i,t}^{K,T}$ is the number of call contracts purchased by non-market makers on day t on underlying stock i with strike price K and maturity T; and $SellCall_{i,t}^{K,T}$, $BuyPut_{i,t}^{K,T}$, and $SellPut_{i,t}^{K,T}$ are the analogous quantities for, respectively, the sale of calls and the purchase and sale of puts. The summations in equation (1) are over all strikes and all maturities greater than 1 week that are available for underlying stock i on trade day t.[8] In the empirical work, we approximate $\partial \ln C_{i,t}^{K,T}/\partial \sigma_{i,t}$ with $(1/C_{i,t}^{K,T}) BlackScholesCallVega_{i,t}^{K,T}$ (and similarly for $\partial \ln P_{i,t}^{K,T}/\partial \sigma_{i,t}$), where the Black-Scholes vega is computed with the volatility of the underlying stock set to the sample volatility from the

[8] We follow the common practice of excluding options with very short maturities. All of our results are robust to including these options.

60 trading days of returns leading up to t. It should be noted that our measure of demand for volatility is observable by market makers who can see the buy and sell orders coming into the market, but it is not observable by other option market participants. Although a non-market maker could use quotation and transaction data in conjunction with the Lee and Ready (1991) algorithm to classify option volume as buyer- or seller-initiated, the classification is only on the order of 80% accurate (Savickas and Wilson (2003)).

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

$$\begin{aligned}
OneDayRV_{i,t} = {} & a + b \cdot D^{\sigma}_{i,t-j} + c \cdot D^{\sigma}_{i,t-j} \cdot Ind_{i,t} \\
& + d \cdot OneDayRV_{i,t-1} + e \cdot OneDayRV_{i,t-1} \cdot Ind_{i,t} \\
& + f \cdot OneDayRV_{i,t-2} + g \cdot OneDayRV_{i,t-2} \cdot Ind_{i,t} \\
& + h \cdot OneDayRV_{i,t-3} + i \cdot OneDayRV_{i,t-3} \cdot Ind_{i,t} \\
& + j \cdot OneDayRV_{i,t-4} + k \cdot OneDayRV_{i,t-4} \cdot Ind_{i,t} \\
& + l \cdot OneDayRV_{i,t-5} + m \cdot OneDayRV_{i,t-5} \cdot Ind_{i,t} \\
& + n \cdot Ind_{i,t} + o \cdot IV_{i,t-1} + p \cdot IV_{i,t-1} \cdot Ind_{i,t} + q \cdot abs\left(D^{\Delta}_{i,t-j}\right) \\
& + r \cdot abs\left(D^{\Delta}_{i,t-j}\right) \cdot Ind_{i,t} + s \cdot optVolume_{i,t-j} \\
& + t \cdot optVolume_{i,t-j} \cdot Ind_{i,t} + u \cdot \ln(stkVolume_{i,t-j}) \\
& + v \cdot \ln(stkVolume_{i,t-j}) \cdot Ind_{i,t} + \varepsilon_{i,t},
\end{aligned} \tag{2}$$

where $OneDayRV_{i,t}$ is a proxy for the realized volatility of stock i on date t, $Ind_{i,t}$ is one if t is an EAD for stock i and zero otherwise, $IV_{i,t}$ is the average implied volatility of the shortest maturity (of at least 5 calendar days) closest to at-the-money (ATM) call and put on underlying stock i on trade day t, $D^{\Delta}_{i,t}$ is the delta-weighted sum of all of the non-market maker option trading volume on underlying stock i on trade day t, $optVolume_{i,t}$ is the number of option contracts that trade on underlying stock i on day t, and $stkVolume_{i,t}$ is the number of shares of stock i that trade on day t. The regression specified in equation (2) is estimated separately for different values of j, and for a fixed j uses the net demand for volatility at time $t-j$ to predict the j-day-ahead realized stock volatility. According to the hypothesis that volatility information trading exists in the option market, we would expect the coefficient estimate on $D^{\sigma}_{i,t-j}$ to be positive and significant for at least some of the j-day-ahead predictive regressions. Moreover, assuming that on average informed traders possess more information about what will occur at EADs than on non-EADs, we would expect to see an incremental predictability from demand for volatility, that is, a positive slope coefficient on the interaction term $D^{\sigma}_{i,t-j} \cdot Ind_{i,t}$ in equation (2). The $Ind_{i,t}$ term that appears by itself on the right-hand side of equation (2) controls for differences in 1-day realized volatility on EADs that are unrelated to volatility demand. The terms involving $OneDayRV_{i,t-n}$ for $n = 1, 2, \ldots, 5$ control for

GARCH type volatility clustering. The $IV_{i,t-1}$ terms control for publicly available information about future realized volatility that should all be impounded into the option prices, and the terms involving $optVolume_{i,t-j}$ and $stkVolume_{i,t-j}$ control for any relationship between option or stock volume and future volatility and also for the possibility that option or stock volume is correlated with option net demand for volatility. The empirical work below will also include specifications that add underlying stock characteristics and interactions of underlying stock characteristics with the $D^{\sigma}_{i,t-j}$ variable in order to investigate potential cross-sectional heterogeneity in volatility information trading.

Clearly, investors trade options for reasons other than possessing private information about the volatility of underlying stocks (e.g., for hedging or for liquidity reasons). In general, this fact should just make it more difficult to detect a relationship between option market demand for volatility and the future volatility of underlying stocks. It does, however, seem important to control for investors trading in the option market on private information that the underlying stock price will increase or decrease. Pan and Poteshman (2006) show that option volume contains information about the future direction of underlying stock price movements. As a result, it is possible that a positive relation between non-market maker net demand for volatility and future stock price volatility could be driven by investors trading on directional information in the option market. This would occur, for example, if investors with positive directional information about an underlying stock buy calls and the stock price subsequently increases. The call purchases 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 and the later decrease in stock price would increase the measure of future realized volatility as well.

We control for option market trading on directional information through the terms in specification (2) involving $abs(D^{\Delta}_{i,t-j})$, the delta-weighted sum of all of the non-market maker option trading volume. When computing this variable, buy volume gets a positive sign, sell volume gets a negative sign, and the delta (positive for calls, negative for puts) is computed under the Black-Scholes assumptions with the volatility of the underlying stock set to the sample volatility from the 60 trading days of returns leading up to t. Hence, $D^{\Delta}_{i,t}$ measures the net equivalent number of shares purchased by non-market makers through their option market trading on underlying stock i on trade date t. Our control uses the absolute value of this quantity, because larger absolute positive (negative) values are consistent with larger quantities of positive (negative) directional trading in the option market.

Aside from option trading that is based on directional information, it is not obvious how option activity that is not motivated by volatility information would bias our tests toward spurious findings of informed volatility trading. For example, option trading motivated by hedging or liquidity concerns should just add noise to our tests, making it more difficult to detect any effects. Nonetheless, we also run our tests after constructing the demand for volatility variable only from option volume that could have been part of straddle trades or that could not have been part of straddle trades. Since volume that is potentially part of straddle trades will have a higher concentration of volatility-based trading than volume that could not have been part of straddle trades, the former should give stronger results than the latter if, indeed, option investors trade on private volatility information.

B. Price Impact and Informational Asymmetry

The second part of our empirical investigation examines the response of option market makers to volatility demand. If market makers believe that option order flow comes in part from investors with private volatility information, then they will increase (decrease) option prices in response to positive (negative) volatility demand.

In order to test for these option pricing implications of informed trading on volatility information, we construct securities out of options that have high sensitivity to realizations of equity volatility and low sensitivity to 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 are as close to the money as possible. This yields close to a "clean" security on volatility: While both call and put options increase in value with increasing volatility, their respective sensitivities to directional moves by the underlying stock are opposite in sign and approximately equal in magnitude if both options are ATM. However, given that we are using exchange-traded options, whose available moneyness and time-to-expiration vary over time, we measure the straddle price in terms of Black-Scholes implied volatility. Specifically, we convert the market-observed call and put option prices into their respective implied volatility, $IV^{c}_{i,t}$ and $IV^{p}_{i,t}$,[9] and measure the price of the security by

$$IV_{i,t} = \frac{1}{2}\left(IV^{c}_{i,t} + IV^{p}_{i,t}\right). \tag{3}$$

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

$$\begin{aligned}(IV_{i,t} - IV_{i,t-1})/IV_{i,t-1} \\ &= \alpha + \lambda D^{\sigma}_{i,t} + D^{\sigma}_{i,t}\left(\lambda^{EAD}_{-5} Ind\,(EAD-5)_{i,t} + \cdots + \lambda^{EAD}_{0} Ind\,(EAD-0)_{i,t}\right. \\ &\quad \left. + \cdots + \lambda^{EAD}_{+5} Ind\,(EAD+5)_{i,t}\right) + \alpha^{EAD}_{-5} Ind\,(EAD-5)_{i,t} + \cdots \\ &\quad + \alpha^{EAD}_{0} Ind\,(EAD-0)_{i,t} + \cdots + \alpha^{EAD}_{+5} Ind\,(EAD+5)_{i,t} + \varepsilon_{i,t},\end{aligned} \tag{4}$$

where $D^{\sigma}_{i,t}$ is the non-market maker net demand for volatility on underlying stock i on trade date t. The corresponding slope coefficient, λ, in equation (4) therefore captures the average price impact of a one-unit increase in volatility

[9] Specifically, we use binomial tree option pricing, taking into account dividend payments and early exercise premiums. See, for example, Harvey and Whaley (1992) for details on extracting volatility information using the dividend-adjusted binomial method on American-style options.

demand. The economic interpretation of this price impact variable could be twofold. While market makers may adjust option prices to protect themselves from informational asymmetry, even in the absence of informational asymmetry they may require a premium (discount) to absorb positive (negative) order flow. As a result, the price impact variable may potentially contain two components: one corresponding to informational asymmetry and the other to pure demand pressure.

To determine whether any of the price impact comes from informational asymmetry, we take advantage of the fact that the noninformational price impact is insensitive to the level of informational asymmetry, while the information-based component depends on the level of informational asymmetry in a crucial way. We exploit this fact in two ways to assess whether any price impact is attributable to volatility information.

First, in addition to the demand for volatility constructed from all option volume, we include another measure of volatility demand, $D_{i,t}^{\sigma,Open}$, which is constructed only from the option volume attributable to non-market makers opening new positions. One would naturally expect that an investor who acquires private information would be more likely to trade on it in the option market by opening rather than closing positions.[10] Hence, the new volatility demand constructed from open volume is expected to have a greater concentration of informed traders. Provided that the market makers have some ability to distinguish the open from the close transactions, the open demand with its higher level of informational asymmetry is predicted to have a higher price impact. Of course, if demand pressure alone is driving the price impact, then the open volume demand variable will not exhibit any additional price impact. The coefficient on $D_{i,t}^{\sigma,Open}$ therefore provides a test to determine whether informational asymmetry contributes to the price impact.[11]

Second, we take advantage of the fact that the days leading up to earnings announcements constitute natural exogenous events for which the level of informational asymmetry is likely to be increasing.[12] If the information-based explanation is an important component of the price impact, then we would observe a pattern of increasing price impact leading up to EADs. On the other hand, if demand pressure is the dominant explanation, then we should not see

[10] Pan and Poteshman (2006) show that this is indeed the case for directional information about underlying stocks.

[11] Market makers do not directly observe in real time whether orders coming into the market open or close positions. However, they do observe the change in open interest at the end of every day, and therefore presumably gain some ability to predict in real time whether order flow opens or closes positions. To the extent that they do not develop this ability, it will be less likely that volatility demand from open volume will have a significant coefficient estimate.

[12] While there may be informational asymmetry about either the directional move of the underlying stock price or 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.

systematic variation in price impact around EADs. Equation (4) tests for this variation by including $Ind(EAD - n)_{i,t}$, which is equal to one if trading day $t + n$ is an EAD for stock i and zero otherwise, and its interaction with the demand variable. For example, $Ind(EAD - 5)_{i,t}$ is one if t is 5 trade days before an EAD for stock i and zero otherwise. The slope coefficient of the interaction term, λ_{τ}^{EAD} for $\tau = -5, \ldots, -1, 0, 1, \ldots, 5$, therefore captures the *incremental* price impact of volatility demand around EADs. In particular, if informational asymmetry contributes to the price impact, λ_{τ}^{EAD} will be positive and significant on days leading up to the EAD, but not for the days after the EAD when information has already been released.

Finally, we add control variables in equation (4) including the (uninteracted) $Ind(EAD - n)_{i,t}$ variables to control for any systematic daily changes in *IV* around EADs that are unrelated to volatility demand. We also include underlying stock characteristics as well as interactions of underlying stock characteristics with the $D_{i,t}^{\sigma}$ variable in order to investigate potential cross-sectional heterogeneity in the price impact of volatility demand.

II. Data

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

A. Data Sources

The data in this paper are drawn from a number of sources. The data used to compute non-market maker net demand for volatility 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 makers sell options to close out existing long option positions. When calculating the demand variable defined by equation (1), the buy volume is composed of the open-buy and close-buy volume and the sell volume is composed of the open-sell and close-sell volume. The non-market maker volume is also subdivided into four classes of investors: firm proprietary traders, public customers of full service brokers, public customers of discount brokers, and other public customers. We use this subdivision when separating volume into the volume that could have been part of straddle trades and the volume that could not have been part of a straddle trade.

Over the period January 2, 1990 through January 31, 1996 we get option price and volume data from the Berkeley Options Database, and from February 1, 1996 through December 31, 2001 we get price, volume, 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 p.m. 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 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.[13]

Stock prices, returns, volumes, and dividends during the entire sample period are obtained from the Center for Research in Security Prices (CRSP). Earnings announcement dates and the data for computing book equity are obtained from Compustat.

B. 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 non-market maker net demand for volatility on stock i on trade date $t-j$, and there must be data available to compute the option-implied volatility on trade date $t-1$. In order for there to be an observation when estimating regression specification (4) for an underlying stock i on a trade date t, there must be data available to construct non-market maker net demand for volatility on stock i on trade date t, and there must be data available to construct the daily change in implied volatility for underlying stock i from trade date $t-1$ to trade date t.

Non-market maker net demand for volatility is considered 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 on underlying stock i on day t.[14] The data to construct the daily implied volatility for stock i on trade date t are available if there exist a call and a put on stock i on trade date t that have the same strike price and time to expiration that meet all of the following three conditions: (1) both the call and put have strictly positive trading volume[15] and implied volatility data available on day t, (2) the time to expiration of the call and the put is between 5 and 50 trading 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 implied volatility by averaging the call and put implied volatilities on day t. Data to construct the change in

[13] However, when calculating implied volatilities OptionMetrics projects dividends rather than using actual realized dividends and interpolates the risk-free rate from a zero curve constructed from LIBOR rates and the settlement prices of CME Eurodollar futures.

[14] The results reported below are similar if the cut off is set to 20 or 100 contracts.

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

implied volatility from day $t-1$ to day t is available if a put and a call that meet the preceding criteria are available on both day t and $t-1$. In this case, the daily change in implied volatility is computed by subtracting the average call and put implied volatilities on day $t-1$ from the average on day t.

For specification (2), we normalize each stock's daily non-market maker net demand for volatility, delta-adjusted net option volume, option volume, one-day realized volatility, and stock volume variables by subtracting the variable's calendar-year mean and then dividing by its calendar-year standard deviation. When one of these variables has fewer than 25 time-series observations for a stock in a calendar year, the stock is deleted for that year. For specification (4), we normalize each stock's daily non-market maker net demand for volatility variable in the same way as for specification (2), and we also de-mean the dependent (i.e., change in implied volatility divided by the level of implied volatility) variable for each underlying stock i by subtracting its calendar-year mean.

Altogether, there are 703,229 stock-days and 2,220 different stocks over our 12-year period that meet the criteria for inclusion when estimating specification (2). There are 12,332 stock-days that fall on earnings announcement dates (EADs) and 1,579 different stocks have observations on at least one EAD. There are an average of 243 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.

C. Summary Statistics

Table I contains summary statistics for the variables used in our main specifications. All statistics in this table are reported before any normalization but after filtering for inclusion in specification (2). The average one-day realized volatility (*oneDayRV*) is 551 basis points or 5.51%. The average implied volatility (*IV*) for all observations is 6,532 basis points or 65.32%. The smallest *IV* is 279 basis points or 2.79% and the largest is 49,999 basis points or 500%. *IV* exhibits strong positive autocorrelation and positive skewness. We also report the summary statistics for the daily change in *IV* (*dIV*) and the daily change in *IV* divided by the level of implied volatility.

The vega weighted non-market maker net demand for volatility (D^σ) has a mean value of -19.25. The fact that this statistic has an average value that is negative implies that on average market makers are long volatility. However, the much larger standard deviation and absolute values of the minimum and maximum of D^σ suggest that it is reasonable to think of the average volatility demand as close to zero. The breakdown of the volatility demand into opening and closing option volume also indicates that non-market makers on average neither demand nor supply a large quantity of volatility when they open or close option positions. In some of the tests below, we compute the volatility according to whether the option volume could or could not have been part of

Table I

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. *OneDayRV* is 10,000 times the difference of an underlying stock's intraday high and low price divided by the closing stock price. Implied volatility (*IV*) is the average implied volatilities of the selected straddle's call and put. *dIV* is daily change in *IV*. Volatility Demand (D^{σ}) is the vega-weighted volatility demand defined in equation (1), Open Volatility Demand is the vega-weighted volatility demand calculated from option volume that opens new positions, and Close Volatility Demand is the vega-weighted volatility demand calculated from option volume that closes existing option positions. Straddle Volatility Demand is the vega-weighted volatility demand from options that could have been part of straddle trades and Nonstraddle Volatility Demand is the vega-weighted volatility demand from options that could not have been part of straddle trades. Abs(D^{Δ}) is absolute net delta-weighted option volume, *optVolume* is total number of option contracts traded, and ln(*stkVolume*) is log of daily stock volume.

	Mean	Std.	Auto	Skew	Kurt	Min.	Max.
OneDayRV (bps)	551	452	0.30	3.04	25.17	0.00	14,185
Implied volatility (IV) (bps)	6,532	3,094	0.83	1.04	4.59	279	49,999
IV change (dIV) (bps)	3.68	476	−0.02	2.45	155	−12,796	33,945
dIV/IV (bps)	27.40	708	−0.02	5.76	156	−7,633	33,777
Volatility demand (D^{σ})	−19.25	2,898	0.08	23.26	5,524	−299,868	703,889
Open volatility demand	84.45	2,931	0.11	16.60	2,638	−334,503	560,901
Close volatility demand	−104	2,244	0.08	−11.26	3,735	−438,727	289,835
Straddle volatility demand	−52.87	1,045	0.06	40.17	8,039	−43,641	222,005
Nonstraddle volatility demand	20.13	1,997	0.06	1.27	612	−149,116	128,863
Abs(D^{Δ})	166	445	0.13	16.56	654	0.00	45,197
optVolume (contracts)	1,810	6,967	0.29	19.70	695	50.00	503,480
ln(stkVolume) (shares)	13.68	1.27	0.54	0.15	3.22	6.91	19.58

straddle trades. Descriptive statistics for the demand variable computed in these different ways are also provided in Table I.

Table II reports the average value of the main variables from Table I for the quantiles of four underlying stock characteristics: relative option volume (*relOptVolume*), historical stock volatility (*histStockVol*), the logarithm of market capitalization (ln(*size*)), and the book-to-market ratio (*BM*). Each of these variables is computed once for each underlying stock for each calendar year. The variable *relOptVolume* is 100 times the ratio of the year's option volume to stock volume, *histStockVol* is 100 times the sample standard deviation computed from the year's daily stock returns, ln(*size*) is the natural logarithm of year-end market capitalization, and *BM* is computed according to the method of Fama and French (1992). In Table II and in the regressions reported below, the value computed for *relOptVolume*, *histStockVol*, and ln(*size*) is associated with the stock during the next calendar year. For *BM*, we follow Fama and French (1992) and associate the value computed from data for a calendar year with the stock starting the following June through the subsequent May. We investigate the *relOptVolume* variable because of the evidence in Chakravarty et al. (2004) that the ratio of option volume to stock volume impacts the degree of price discovery in the option market. We examine *histStockVol* because of the centrality to volatility in the option markets. The variables ln(*size*) and *BM* are included, because of the widespread interest in these stock characteristics.

The summary statistics in Table II show that the main volatility demand variable does not display any clear pattern across the quantiles for any of the four stock characteristic variables. The same is true for the volatility demand variables constructed from open or close volume or from trades that could or could not have been part of straddle trades.

Table III reports the cross-sectional correlation coefficients for the main variables in Table I. Implied volatility (*IV*) has close to zero correlation with volatility demand (D^{σ}). The daily change in implied volatility (*dIV*), on the other hand, is positively correlated with volatility demand (0.22).

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 plot is the average value of the variable across all observations. The first panel indicates that, as expected, stocks have higher realized volatility on EADs. The second panel reports the daily change in implied volatility divided by the level of implied volatility. (Since in the regression analysis below we use this quantity measured in basis points, that is how we report it here—for example, if the daily change in implied volatility is 1% of the level of implied volatility, the observation is recorded as 100 basis points.) Panel 2 indicates that before EADs, daily changes in implied volatility are all positive. The largest average daily change occurs one day before the EAD. On the EAD and for the following week 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. After about a week, the bars are not far from the sample mean.

Panels 3 through 6 present information on the trading patterns in the stock and option market around EADs. Interestingly, the volatility demand depicted in Panel 3 is positive before the EAD and negative after the EAD. Hence, non-market makers are buying volatility before EADs and selling it after EADs. Panels 5 and 6 indicate that increased activity both begins and ends sooner

Table II

Summary Statistics Broken Down by Stock Characteristics

This table reports the average values from the beginning of 1990 through the end of 2001 of a number of variables for the quantiles of various stock characteristics. The variables are *oneDayRV* (10,000 times the difference of an underlying stock's intraday high and low price divided by the closing stock price), *IV* (the average implied volatilities of a selected straddle's call and put), *dIV* (the daily change in *IV*), *dIV/IV* (the daily change in the implied volatility divided by the level of implied volatility), D^{σ} (the vega-weighted volatility demand defined in equation (1)), Open Volatility Demand (the vega-weighted volatility demand calculated from option volume that opens new positions), Close Volatility Demand (the vega-weighted volatility demand calculated from option volume that closes existing option positions), Straddle Volatility Demand (the vega-weighted volatility demand calculated from option volume that could have been part of straddles), and Nonstraddle Volatility Demand (the vega-weighted volatility demand calculated from option volume that could not have been part of straddles). The stock characteristics are: *relOptVolume* (100 times the ratio of option volume to stock volume over the previous calendar year), *histStockVol* (100 times the sample standard deviation of a stock over the past calendar year), ln(size) (the natural logarithm of the market capitalization of the stock at the end of the previous calendar year), and *BM* (the stock's book-to-market ratio as in Fama and French (1992)).

	Quantiles				
	Low	2	3	4	High
Panel A: Relative Option Volume					
OneDayRV (bps)	635	603	602	544	500
Implied volatility (IV) (bps)	7187	6567	7070	6519	6129
IV change (dIV) (bps)	4.21	4.01	3.97	2.15	0.45
dIV/IV (bps)	36.36	37.05	27.02	24.85	23.80
Volatility demand (D^{σ})	−19.72	−14.30	2.33	−35.47	−20.60
Open volatility demand	31.38	44.10	40.57	2.26	161.36
Close volatility demand	−51.10	−58.40	−38.24	−37.73	−181.96
Straddle volatility demand	−36.96	−51.63	−39.72	−61.98	−51.87
Nonstraddle volatility demand	−4.30	70.51	−16.61	−28.10	39.49
Panel B: Historical Stock Volatility					
OneDayRV (bps)	356	386	519	608	743
Implied volatility (IV) (bps)	4438	4791	6343	7087	8446
IV change (dIV) (bps)	4.72	8.05	4.41	2.28	−5.39
dIV/IV (bps)	40.20	42.71	28.17	23.25	10.81
Volatility demand (D^{σ})	−33.00	−19.42	−32.99	−35.22	14.31
Open volatility demand	115.42	181.60	70.89	0.61	64.73
Close volatility demand	−148.42	−201.03	−103.88	−35.83	−50.42
Straddle volatility demand	−37.14	−84.72	−59.86	−57.61	−31.04
Nonstraddle volatility demand	113.24	21.69	9.41	−0.62	−7.39

(*continued*)

Table II—*Continued*

	Quantiles				
	Low	2	3	4	High
Panel C: ln(size)					
OneDayRV (bps)	746	697	548	479	391
Implied volatility (IV) (bps)	8276	8124	6691	5964	4899
IV change (dIV) (bps)	−10.52	3.49	4.24	6.07	2.93
dIV/IV (bps)	13.86	26.25	25.81	29.07	32.34
Volatility demand (D^{σ})	−17.41	8.51	−11.58	−39.98	−31.16
Open volatility demand	4.67	60.87	68.21	−11.85	195.30
Close volatility demand	−22.08	−52.37	−79.79	−28.13	−226.46
Straddle volatility demand	−53.97	−32.60	−64.67	−41.21	−59.84
Nonstraddle volatility demand	−17.52	13.40	−24.86	−7.43	61.90
Panel D: Book-to-Market Ratio					
OneDayRV (bps)	585	556	523	477	591
Implied volatility (IV) (bps)	6737	6531	6308	5748	6972
IV change (dIV) (bps)	−0.10	6.42	4.34	0.87	−1.50
dIV/IV (bps)	21.09	31.77	30.94	26.26	26.68
Volatility demand (D^{σ})	−41.16	−20.50	−19.75	20.31	−16.43
Open volatility demand	61.08	79.98	70.06	157.37	30.07
Close volatility demand	−102.24	−100.48	−89.81	−137.06	−46.50
Straddle volatility demand	−54.27	−51.02	−56.78	−44.62	−57.39
Nonstraddle volatility demand	30.41	12.95	−5.22	42.04	6.81

in the option market than the stock market. For example, there is a sizeable increase in option volume but not in stock volume before the EAD. The increased option volume, however, lasts only until day +1 while the stock volume is still elevated on day +4. The unique time pattern in the demand for volatility is also noteworthy. Panel 3 shows that it increases substantially in the days before the EAD and declines by the EAD. These patterns suggest that volatility and directional trading behave differently around EADs.

III. Results

A. Information in Option Volume for Future Stock Price Volatility

As detailed in Section I, our first empirical specification is designed to test whether non-market maker net demand for volatility in the option market predicts the future volatility of underlying stocks. Specifically, equation (2) is estimated after filtering observations and constructing variables as described in Section II. Following Alizadeh, Brandt, and Diebold (2002), the $OneDayRV_{i,t}$ proxy 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.[16] We perform

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

Table III

Correlation Coefficients

This table reports the correlation coefficients for a number of variables over the January 1990 through December 2001 time period. *OneDayRV* is 10,000 times the difference of an underlying stock's intraday high and low price divided by the closing stock price. *IV* is the average implied volatilities of the selected straddle's call and put. The *dIV* is daily change in *IV*. Volatility Demand (D^{σ}) is the vega-weighted volatility demand defined in equation (1). Open Volatility Demand, Close Volatility Demand, Straddle Volatility Demand, and Nonstraddle Volatility Demand are volatility demand constructed only from, respectively, open or close option volume, or option volume that may have been or could not have been part of straddle trades. *Abs*(D^{Δ}) is absolute net delta-weighted option volume, *optVolume* is total number of option contracts traded, and ln(*stkVolume*) is log of daily stock volume.

	One DayRV	*IV*	*dIV*	*dIV*/*IV*	Vol. Dem.	Open Vol. Dem.	Close Vol. Dem.	Straddle Vol. Dem.	Nonstraddle Vol. Dem.	Abs(D^{Δ})	*optVolume*
Implied volatility (IV)	0.39										
IV change (dIV)	0.14	0.17									
dIV/IV	0.15	0.17	0.97								
Volatility demand (D^{σ})	0.07	0.01	0.22	0.22							
Open volatility demand	0.09	0.02	0.19	0.20	0.76						
Close volatility demand	−0.02	−0.02	0.07	0.07	0.42	−0.21					
Straddle volatility demand	0.03	−0.02	0.12	0.13	0.19	0.17	0.05				
Nonstraddle vol. demand	0.00	−0.03	0.07	0.08	0.32	0.23	0.14	0.08			
Abs(D^{Δ})	0.17	0.08	0.03	0.04	−0.03	0.00	−0.05	−0.02	0.05		
OptVolume	0.27	0.15	0.07	0.08	0.01	0.06	−0.08	−0.01	0.04	0.55	
ln(stkVolume)	0.47	0.29	0.04	0.05	0.03	0.06	−0.04	−0.02	0.00	0.27	0.44

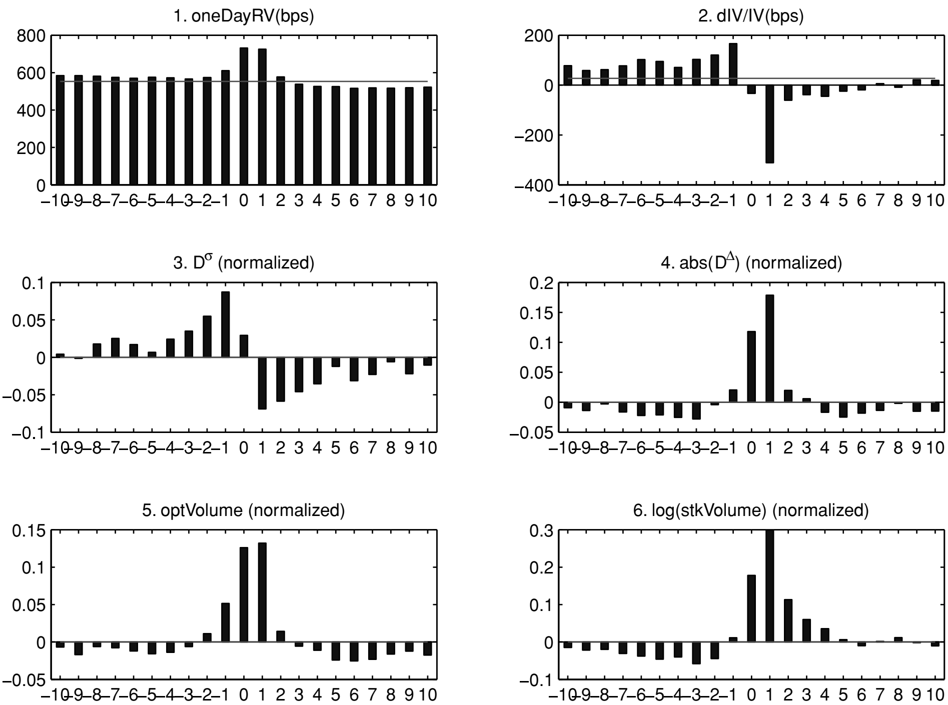

Figure 1. Average value of variables before and after earnings announcement dates. This figure reports the average value of variables at various numbers of trading days relative to earnings announcement dates. The horizontal lines correspond to the average value of the variable across the entire sample. *OneDayRV* is 10,000 times the difference of an underlying stock's intraday high and low prices divided by the closing stock price. The *dIV*/*IV* is this daily change in the implied volatility of a short-maturity, close-to-the-money straddle divided by the level of that straddle's implied volatility. This quantity is reported in basis points, consistent with how it is used in the regression analysis. Volatility demand (D^{σ}) is the vega-weighted volatility demand defined in equation (1), abs(D^{Δ}) is absolute net delta-weighted option volume, *optVolume* is total number of option contracts traded, and ln(*stkVolume*) is the logarithm of daily stock volume.

pooled regressions and compute t-statistics from robust standard errors that correct for cross-sectional correlation in the data.

Table IV summarizes the main results. For all values of $j = 1, 2, 3, 4, 5$ the coefficient on the non-market maker net demand for volatility variable, $D^{\sigma}_{i,t-j}$, is positive and significant, indicating that, indeed, option volume contains information about the future volatility of the underlying stock for at least 5 trading days into the future. The reported coefficient on the interaction term with the EAD indicator also shows that on the day before the EAD, there is an additional, significant increase in the informational content of the option volume.

Table IV also reports the coefficients on the control variables, including the proxy for the realized volatilities on days $t-5$ through $t-1$. Consistent with the well-known volatility clustering effect from the ARCH/GARCH literature, the

Table IV

The Information in Volatility Demand for Future Realized Volatility of the Underlying Stock

This table reports estimates from pooled regressions over 1990 through 2001. The dependent variable, $OneDayRV_{i,t}$, is a proxy for the realized volatility of 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 closing stock price. The net demand variable, D^{σ}, is the demand for volatility in the option market for underlying stock i on trade day $t-j$. The *IV* variable is the implied volatility for the underlying stock on trade day $t-1$ computed from a short-maturity, close-to-the-money put-call pair. The D^{Δ} variable is the net equivalent number of shares of underlying stock i bought in the option market on day $t-j$. The *optVolume* variable is the total number of contracts of options on underlying stock i traded on day $t-j$. The *stkVolume* variable is the number of shares of stock i that trade on day $t-j$. The results are presented for $j = 1, \ldots, 5$. The *Ind* variable is one if trade day t is an earnings announcement day for stock i and zero otherwise. The second row of the table indicates the time at which that column's variable is measured. The third row of the table indicates whether that column's variable is interacted with this indicator variable. The parentheses contain t-statistics computed from robust standard errors that correct for cross-sectional correlation in the data.

		D^{σ}		*OneDayRV*											*IV*		abs(D^{Δ})		*OptVolume.*		ln(*stkVolume*)			
			$t-j$		$t-1$		$t-2$		$t-3$		$t-4$		$t-5$	Ind		t		$t-j$		$t-j$		$t-j$	Adj.	
j	Const.	$t-j$	× Ind	$t-1$	× Ind	$t-2$	× Ind	$t-3$	× Ind	$t-4$	× Ind	$t-5$	× Ind	t	$t-1$	× Ind	$t-j$	× Ind	$t-j$	× Ind	$t-j$	× Ind	R^2	Obs
1	−2.45	10.42	8.40	0.21	−0.04	0.06	−0.01	0.04	0.03	0.03	−0.01	0.02	0.02	139.52	0.04	0.01	1.24	−3.87	0.43	1.43	6.54	−7.56	0.15	703,229
	(−0.89)	(11.64)	(2.35)	(7.96)	(−1.35)	(8.81)	(−0.43)	(5.28)	(1.10)	(4.09)	(−0.33)	(4.00)	(0.84)	(24.12)	(19.85)	(1.41)	(2.16)	(−1.08)	(0.32)	(0.26)	(2.04)	(−1.37)		
2	−2.30	5.95	2.68	0.23	−0.06	0.07	−0.01	0.04	0.00	0.03	0.02	0.02	0.00	136.69	0.04	0.01	0.28	−1.07	−3.90	−8.19	0.18	6.65	0.15	683,212
	(−0.88)	(8.69)	(0.81)	(8.97)	(−1.93)	(10.52)	(−0.71)	(5.13)	(0.11)	(4.70)	(1.11)	(3.90)	(−0.14)	(23.89)	(18.08)	(2.65)	(0.47)	(−0.27)	(−3.07)	(−1.43)	(0.14)	(1.18)		
3	−2.32	5.07	−2.87	0.23	−0.05	0.07	−0.02	0.04	0.00	0.03	0.01	0.03	0.03	141.16	0.04	0.01	0.12	−2.08	−3.26	2.50	−3.16	−2.89	0.16	678,028
	(−0.88)	(7.34)	(−0.75)	(8.81)	(−1.54)	(8.20)	(−0.75)	(5.84)	(0.07)	(5.00)	(0.39)	(4.88)	(1.43)	(22.24)	(19.57)	(2.17)	(0.22)	(−0.50)	(−2.56)	(0.49)	(−2.49)	(−0.55)		
4	−2.28	3.40	−0.08	0.25	−0.05	0.06	−0.02	0.04	0.01	0.03	−0.01	0.03	0.02	139.26	0.04	0.01	0.80	0.54	−4.70	9.12	−0.68	−8.28	0.16	675,552
	(−0.90)	(5.16)	(−0.01)	(29.29)	(−2.26)	(8.25)	(−0.96)	(5.10)	(0.43)	(4.40)	(−0.23)	(4.47)	(0.79)	(24.39)	(26.13)	(3.09)	(1.56)	(0.11)	(−3.92)	(1.60)	(−0.58)	(−1.67)		
5	−2.18	2.13	11.09	0.24	−0.05	0.07	−0.01	0.04	0.00	0.03	0.02	0.03	−0.01	134.98	0.04	0.02	1.36	−3.69	−5.47	4.75	−0.32	1.03	0.17	673,615
	(−0.84)	(3.99)	(2.62)	(15.22)	(−1.83)	(9.70)	(−0.50)	(4.63)	(−0.12)	(4.90)	(0.94)	(5.15)	(−0.52)	(23.31)	(23.27)	(3.13)	(2.46)	(−0.85)	(−4.96)	(0.99)	(−0.30)	(0.22)		

coefficients on the lagged realized volatilities are positive and significant. We also include the lagged implied volatility to control for the information already contained in the option price. Consistent with the findings in the literature on the informational content of implied volatility, the coefficients on the *IV* control variable are positive and significant. This fact indicates that, not surprisingly, the implied volatility at the end of day $t-1$ contains information about the realized volatility on day t. The inclusion of this control variable also allows us to conclude that the volatility demand contains information about future volatility beyond that present in implied volatility. It is commonly believed that implied volatility impounds all publicly available information about the future volatility of the underlying stock. Since the market makers can observe volatility demand, our results suggest that at least some information about future volatility that is observable to an important set of option market participants is not immediately reflected in option prices.[17] Finally, the coefficient for abs(D^{Δ}), which controls for option market trading on private directional information, is positive but more often than not insignificant. The comparison between the predictability of D^{σ} and abs(D^{Δ}) is interesting since both demand variables are constructed from the same set of option trading volumes and are different only in that D^{σ} is vega weighted while D^{Δ} is delta weighted. The lack of predictability of abs(D^{Δ}) indicates that by weighting the option volume by how sensitive each option contract is to volatility information, we pick up the volatility-related information from the option trading volume.

In Table V, we further separate the total non-market maker net demand for volatility into two groups by taking advantage of the fact that our data set distinguishes non-market maker volume that opens new option positions from non-market maker volume that closes existing positions. Panels A and B of Table V report estimation results when the net demand for volatility is computed from only open or close option volume, respectively. For the sake of brevity, Table V does not report the coefficient estimates and t-statistics for the *Ind*, lagged *OneDayRV*, *IV*, D^{Δ}, *optVolume*, and ln(*stkVolume*) control variables. The omitted coefficient estimates and t-statistics are similar to those reported in Table IV. The main effect is considerably stronger for open than for close volume. For example, when $j = 1$ the coefficient on open volume net volatility demand is 8.51 (t-statistic $= 11.43$). On the other hand, when close volume is used, the corresponding coefficient estimate is just 4.78 (t-statistic $= 7.09$).

These results are interesting for two reasons. First, investors who trade on volatility information in the option market are more likely to do so by opening new option positions; to do so by closing existing positions requires that a trader who obtains private volatility information has existing option positions on the underlying stock that the information indicates should be closed. Second, the fact that the main result is considerably stronger for open than close volume suggests that microstructure or other mechanical effects such as market maker

[17] A caveat here is that implied volatility should subsume all other publicly observable variables as a forecaster of the realized volatility over the life of the options from which the volatility is implied. Our tests, however, predict realized volatility only over the next trading day.

Table V

The Information in Open and Close Volatility Demand for Future Realized Volatility of the Underlying Stock

This table reports estimates from pooled regressions over 1990 through 2001. The dependent variable, $OneDayRV_{i,t}$, is a proxy for the realized volatility of 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 closing stock price. The net demand variable, D^{σ}, is the demand for volatility in the option market for underlying stock i on trade day $t-j$. In the two panels, it is computed either from open or close option volume. The *IV* variable is the implied volatility for the underlying stock on trade day $t-1$ computed from a short-maturity, close-to-the-money put-call pair. The D^{Δ} variable is the net equivalent number of shares of underlying stock i bought in the option market on day $t-j$. The *optVolume* variable is the total number of contracts of options on underlying stock i traded on day $t-j$. The *stkVolume* variable is the number of shares of stock i that trade on day $t-j$. Each panel presents results for $j = 1, \ldots, 5$. The *Ind* variable is one if trade day t is an earnings announcement day for stock i and zero otherwise. The second row of the table indicates the time at which that column's variable is measured. The third row of the table indicates whether that column's variable is interacted with this indicator variable. The parentheses contain t-statistics computed from robust standard errors that correct for cross-sectional correlation in the data.

	D^{σ}			
j	$t-j$	$t-j \times Ind$	Adj. R^2	Obs.
Panel A: Net Volatility Demand from Open Option Volume				
1	8.51	6.27	0.15	703,229
	(11.43)	(1.85)		
2	4.55	1.01	0.14	683,212
	(7.19)	(0.30)		
3	4.81	2.05	0.16	678,028
	(7.21)	(0.49)		
4	3.13	−0.71	0.16	675,552
	(5.34)	(−0.18)		
5	1.09	12.05	0.16	673,615
	(2.03)	(2.79)		
Panel B: Net Volatility Demand from Close Option Volume				
1	4.78	5.59	0.15	703,180
	(7.09)	(1.58)		
2	3.10	7.83	0.14	683,164
	(5.05)	(2.17)		
3	1.23	−8.11	0.16	677,969
	(2.46)	(−2.14)		
4	1.18	3.32	0.16	675,501
	(2.28)	(0.40)		
5	1.80	3.16	0.16	673,570
	(3.31)	(0.74)		

hedging are unlikely to account for the observed future changes in the volatility of the underlying stocks.[18] For example, market makers will hedge their new

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

option positions in the same way regardless of whether they result from non-market makers opening or closing option positions. For both of these reasons, the stronger findings for open than close volume provide evidence that our main result is driven by investors bringing private volatility information to the market.

We generate further evidence on whether volatility information trading lies behind our results by identifying option volume that is likely to have higher and lower concentrations of informed volatility trading. Some option market trades represent bets on both the level and the volatility of the underlying stock. For example, an investor who buys a naked call benefits from an increase in the level of the underlying stock price and also from an increase in its volatility. Other trades, however, bet primarily on increases or decreases in volatility, and, presumably, informed volatility traders would tend to make such trades. The leading example of these trades is a straddle where an investor buys or sells a call and a put with the same strike price and time to expiration. If the predictability that we identify in the option volume indeed has its source in informed volatility trading, then the predictability should be stronger from volume that has a higher concentration of straddle trading.

We test this hypothesis by separating the option volume into that that could have been part of straddle trades and that that could not have been part of straddles. We define volume that could have been part of a straddle trade to be matching call and put volume on a given trading day. In order for call and put volume to be matching, it must be on the same underlying stock with the same strike price and time to expiration. In addition, it must be from the same class of investor (i.e., firm proprietary traders, discount customers, full service customers, or other public customers) and match on whether it is buy or sell volume and also on whether it is open or close volume. Finally, when the number of contracts of call and put volume that meet these criteria is not the same, the smaller number of contracts of both the call and put volume are counted as potentially part of straddle trades. All volume that is not potentially part of straddle trades is defined as volume that could not have been part of straddle trades.[19]

Table VI reports the respective predictability when the net volatility demand is computed from volume that could have been part of straddles and volume that could not have been part of straddles. Again, all controls specified in equation (2) are included in the estimation but not reported in the table. For all five values of j, the predictability is stronger when demand is computed from

[19] In order to illustrate our classification, suppose that on a given trade day there are five contracts of firm proprietary trader open buy IBM call volume with strike price 20 and expiration next month, and eight contracts of firm proprietary open buy IBM put volume with strike price 20 and expiration next month. In this case, all five contracts of the call volume and five of the eight contracts of the put volume will be classified as potentially part of straddle trades while the other three contracts of put volume will be classified as not part of straddle trades. Although not all volume classified as potentially part of straddle trades is in fact part of straddle trades (e.g., if the call and put volume comes from different investors within the same investor class), this volume certainly has a higher concentration of straddles than the volume classified as not part of straddles trades because the latter contains no straddle trading at all.

Table VI

The Information in Potential Straddle and Nonstraddle Volatility Demand for Future Realized Volatility of the Underlying Stock Volume

This table reports estimates from pooled regressions over 1990 through 2001. The dependent variable, $OneDayRV_{i,t}$, is a proxy for the realized volatility of 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 closing price. The net demand variable, D^{σ}, is the demand for volatility in the option market for underlying stock i on trade day $t-j$. In addition to the variables reported in the table, *OneDayRV* for $t-1$ through $t-5$, *IV*, D^{Δ}, *optVolume*, and ln(*stkVolume*) both by themselves and interacted with the *Ind* indicator variable that is one if day t is an earnings announcement day for stock i are included as controls. The *Ind* indicator variable by itself is also included as a control. The second row of the table indicates the time at which that column's variable is measured. The third row of the table indicates whether that column's variable is interacted with this indicator variable. Panels A and B contain results from running the regressions where the net demand variable, D^{σ}, is constructed from, respectively, (1) only option volume that could have been part of straddles, and (2) only option volume that could not have been part of straddles. Each panel presents results for $j = 1, \ldots, 5$. The parentheses contain t-statistics computed from robust standard errors that correct for cross-sectional correlation in the data.

	D^{σ}			
j	$t-j$	$t-j \times Ind$	Adj. R^2	Obs.
Panel A: Volatility Demand from Volume That Could Have Been Part of Straddles				
1	9.18	10.09	0.19	268,385
	(8.94)	(1.99)		
2	3.77	−4.63	0.19	268,422
	(5.15)	(−0.80)		
3	3.19	−0.13	0.19	268,436
	(4.79)	(−0.02)		
4	1.88	9.06	0.19	268,440
	(2.69)	(0.65)		
5	1.55	−2.01	0.19	268,424
	(2.12)	(−0.32)		
Panel B: Volatility Demand from Volume That Could Not Have Been Part of Straddles				
1	3.63	14.13	0.19	268,385
	(4.98)	(2.69)		
2	1.73	−5.35	0.19	268,422
	(2.63)	(−1.08)		
3	0.87	−0.91	0.19	268,436
	(1.45)	(−0.14)		
4	0.67	−0.39	0.19	268,440
	(0.95)	(−0.07)		
5	0.41	10.48	0.19	268,424
	(0.62)	(1.72)		

volume that could have been part of straddles than when demand is computed from volume that could not have been part of straddles. For example, when $j = 1$, the coefficient estimate on D^{σ} is 9.18 (t-statistic = 8.94) when demand is computed from volume that could have been part of straddles and 3.63

(t-statistic $= 4.98$) when computed from volume that could not have been part of straddles. The stronger results from volume that is potentially part of straddles support the proposition that the predictability has its source in volatility information trading.

As discussed in Section I, it is important to examine whether the positive relation between non-market maker net demand for volatility and future realized volatility is driven by option market trading on private directional information. For this reason, the specification in equation (2) includes the D^{Δ} variables to control for directional trading. To further investigate whether option market trading on directional information is likely to be an important factor in the previous results, we rerun the tests from Table IV separately on underlying stocks that have open buy volume put-call ratios in the bottom, middle, and top terciles. That is, on each trading day we assign observations to terciles based on the open buy volume put-call ratio of the underlying stocks and then run the pooled regression separately on the observations that fall into each of the terciles. We run these tests because Pan and Poteshman (2006) show that the open buy volume 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 play an important role in generating the results reported in Table IV, then we would expect the findings to be weaker for the middle tercile observations (for which there is relatively little directional information in the option volume) and stronger in the low (high) tercile observations, which contain a good deal of information on whether stock prices are going to subsequently increase (decrease).

The results for the three open buy volume put-call ratio terciles are reported in Table VII. As in Pan and Poteshman (2006), stock trading dates are included in these regressions when there are at least 50 contracts of open buy option volume. For all five values of j the middle put-call ratio tercile regression has the largest coefficient on the net demand variable. Hence, there is no evidence that the relation between non-market maker net demand for volatility and future realized volatility is weaker when there is less directional information in the option volume. Indeed, it appears that the relation may be stronger when there is less directional information. We conclude that it is unlikely that our evidence that option volume is predictive for future volatility is driven by directional predictability in the option volume.

Finally, we examine the cross-sectional variation in the volatility demand predictability using observable characteristics of the underlying stock. Specifically, we add to the specification in equation (2) the following cross-sectional variables, which were defined in Subsection II.C: *relOptVolume* (the ratio of option volume to stock volume), *histStockVol* (the annual realized stock volatility), ln(*size*) (the logarithm of firm size), and *BM* (the book-to-market ratio). We also add their interactions with volatility demand to the predictive analysis so that we can examine whether the predictability that we document varies across different firm characteristics.

The results are presented in Table VIII, which again for the sake of brevity omits the coefficient estimates and t-statistics for the control variables. The

Table VII

The Information in Volatility Demand for Future Realized Volatility of the Underlying Stock: Underlying Stocks with Different Open Buy Put-Call Ratios

This table reports estimates from pooled regressions over 1990 through 2001. The dependent variable, $OneDayRV_{i,t}$, is a proxy for the realized volatility of 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 closing price. The net demand variable, D^{σ}, is the demand for volatility in the option market for underlying stock i on trade day $t-j$. In addition to the variables reported in the table, *OneDayRV* for $t-1$ through $t-5$, *IV*, D^{Δ}, *optVolume*, and ln(*stkVolume*) are included as controls both by themselves and interacted with the *Ind* indicator variable that is one if day t is an earnings announcement day for stock i. The *Ind* indicator variable is also included as a control. The second row of the table indicates the time at which that column's variable is measured. The third row of the table indicates whether that column's variable is interacted with this indicator variable. Panels A through C contain the results from running the regressions on observations with underlying stocks in the lowest (1), middle (2), and highest (3) terciles of daily open buy volume put-call ratio for underlying stocks, and each panel presents results for $j = 1, \ldots, 5$. The parentheses contain t-statistics computed from robust standard errors that correct for cross-sectional correlation in the data.

	D^{σ}			
j	$t-j$	$t-j \times Ind$	Adj. R^2	Obs.
		Panel A: Low PC Tercile		
1	8.96	3.31	0.17	116,576
	(8.92)	(0.51)		
2	4.57	−4.97	0.17	113,946
	(5.42)	(−0.80)		
3	4.50	−8.58	0.17	113,041
	(5.25)	(−1.38)		
4	3.52	10.86	0.17	112,517
	(4.03)	(1.39)		
5	2.12	8.65	0.17	112,292
	(2.92)	(1.27)		
		Panel B: Middle PC Tercile		
1	12.46	9.08	0.16	188,017
	(7.96)	(1.27)		
2	6.64	4.94	0.16	185,857
	(6.20)	(0.79)		
3	4.94	−6.81	0.16	185,029
	(4.31)	(−0.89)		
4	3.84	−2.83	0.16	184,541
	(3.76)	(−0.36)		
5	2.56	18.36	0.18	184,190
	(2.98)	(2.17)		
		Panel C: High PC Tercile		
1	8.17	11.75	0.16	184,800
	(9.12)	(1.82)		
2	3.89	0.87	0.17	180,865
	(5.50)	(0.16)		
3	4.45	−0.54	0.18	179,709
	(5.30)	(−0.07)		
4	2.00	3.77	0.18	179,326
	(3.06)	(0.28)		
5	0.78	15.78	0.16	178,748
	(1.07)	(1.90)		

Table VIII

Cross-sectional Heterogeneity in the Information in Volatility Demand for Future Realized Volatility of the Underlying Stock

This table reports estimates from pooled regressions over 1990 through 2001. The dependent variable, $OneDayRV_{i,t}$, is a proxy for the realized volatility of 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 closing stock price. The net demand variable, D^{σ}, is the demand for volatility in the option market for underlying stock i on trade day $t-j$. The D^{σ} measure appears alone and is also interacted with an indicator variable and four stock characteristics: *relOptVolume* (100 times the ratio of option volume to stock volume over the previous calendar year), *histStockVol* (100 times the sample standard deviation of a stock over the past calendar year), ln(*size*) (the natural logarithm of the market capitalization of the stock at the end of the previous calendar year), and *BM* (the stock's book-to-market ratio as in Fama and French (1992)). In addition to the variables reported in the table, *OneDayRV* for $t-1$ through $t-5$, *IV*, D^{Δ}, *optVolume*, and ln(*stkVolume*) are included as controls both by themselves and interacted with the *Ind* indicator variable. The uninteracted *Ind* indicator, *relOptVolume*, *histStockVol*, ln(*size*), and *BM* variables are also included as controls. The *Ind* variable is one if trade day t is an earnings announcement day for stock i and zero otherwise. The second row of the table indicates the time at which that column's variable is measured. The third row of the table indicates whether that column's variable is interacted with the indicator variable or a stock characteristic variable. The parentheses contain t-statistics computed from robust standard errors that correct for cross-sectional correlation in the data.

	D^{σ}							
j	$t-j$	$t-j$ $\times$ *Ind*	$t-j$ $\times$ *relOptVolume*	$t-j$ $\times$ *histStockVol*	$t-j$ $\times$ ln(size)	$t-j$ $\times$ *BM*	Adj. R^2	Obs.
1	10.87	8.71	−6.00	1.28	−1.69	−7.67	0.15	703,229
	(3.62)	(2.45)	(−1.85)	(1.82)	(−5.14)	(−4.98)		
2	8.40	2.71	−0.60	0.27	−1.40	−5.96	0.15	683,212
	(4.84)	(0.82)	(−0.18)	(0.73)	(−5.00)	(−4.51)		
3	5.18	−3.00	−4.51	0.77	−1.10	−3.12	0.16	678,028
	(3.60)	(−0.78)	(−1.39)	(2.01)	(−4.01)	(−2.47)		
4	3.07	0.00	−4.69	0.66	−0.85	−1.19	0.16	675,552
	(1.60)	(−0.00)	(−1.49)	(1.59)	(−2.80)	(−1.00)		
5	3.40	11.17	−2.38	−0.07	−0.27	−1.76	0.16	673,615
	(2.61)	(2.64)	(−0.86)	(−0.23)	(−1.05)	(−1.52)		

coefficient on the term that interacts D^{σ} with ln(*size)* is negative for all values of j and statistically significant for $j = 1, 2, 3$, and 4. The negative coefficient estimate indicates that there is less private volatility information per unit of volatility demand for larger stocks. This result is consistent with the idea that information flow is more efficient for larger stocks. The *BM* interaction term also has all negative coefficient estimates that are significant for $j = 1, 2$, and 3. This finding suggests that investors bring more volatility information to the option market for glamour firms. The estimates for the *relOptVolume* and *histStockVol* terms are mostly insignificant. The *relOptVolume* estimates are all negative. To the extent that these insignificant negative signs have any meaning, they are consistent with there being greater volatility information per unit of volatility demand for underlying stocks that have less option market relative to stock market trading. This may be because stocks with relatively more option market trading have a higher baseline of option market activity unrelated to private volatility information. The point estimates for the *histStockVol* interaction term are mostly positive. If the sign of these estimates actually is meaningful despite their lack of statistical significance, it would indicate that there is a higher concentration of option trading based on private volatility information on higher volatility stocks.

B. Price Impact and Informational Asymmetry

The previous subsection demonstrates that non-market maker net demand for volatility predicts the future volatility of underlying stocks. This fact was interpreted as evidence that investors use the option market to trade on volatility information. It is therefore natural to explore the pricing consequences of investors bringing volatility information to the option market. We next investigate whether option prices are impacted by market makers "protecting" themselves from investors who possess private information about the future volatility of underlying stocks.

The results of estimating equation (4) are reported in Table IX. Once again, we perform pooled regressions and compute t-statistics from robust standard errors that correct for cross-sectional correlation in the data. The dependent variable is the daily *percent* change in the implied volatility in units of basis points. As reported in the first column of Table IX, the coefficient on the non-market maker net demand for volatility variable is 154 basis points and is highly significant, implying that on average a one-standard deviation increase in volatility demand increases implied volatility by over 1.5%.

In order to investigate cross-sectional heterogeneity in the price impact of volatility demand, specification (4) includes the four underlying stock characteristic variables along with their interactions with the demand variable. The only one of these terms that has a significant coefficient estimate is the one that interacts volatility demand with firm size. The negative coefficient on this interaction term indicates that the price impact per unit of volatility demand is greater for smaller stocks. Once again, this result is consistent with smaller firms having less efficient information flow.

As discussed in Subsection I.B, the positive and significant price impact coefficient on the volatility demand variable could be driven by two components: demand pressure and informational asymmetry. We investigate in two ways whether informational asymmetry plays an important role in producing the price impact. Both approaches take advantage of the variation in informational asymmetry across time and across different kinds of option trading volume.

First, we examine the price impact of a unit of volatility demand as information asymmetry increases leading up to EADs. The coefficients on the interaction terms $D^{\sigma} \times Ind(EAD + n)$ give the incremental price impact of a unit of volatility demand associated with it being day n relative to an EAD. As shown in the first column of Table IX, in the 5 days leading up to the EAD (i.e., when $n = -5, -4, -3, -2$, and -1), the marginal impact of a unit of volatility demand is positive with a coefficient ranging between 23 and 63. Furthermore, the

Table IX

Price Impact per Unit of Volatility Demand

This table reports estimates from pooled regressions over 1990 through 2001. The dependent variable is 10,000 times the daily change in implied volatility divided by the level of the implied volatility for underlying stock i on trade date $t-1$. The D^{σ} variable is the net non-market maker demand for volatility in the option market for underlying stock i on trade day t. $D^{\sigma,Open}$ is the same computed only from option volume that opens new option positions. *relOptVolume* is 100 times the option volume divided by the stock volume, *histStockVol* is 100 times the standard deviation of daily returns from the past year, *size* is market capitalization, and *BM* is the book-to-market ratio. The $Ind(EAD-n)$ variable is one if trade day $t+n$ is an earnings announcement for stock i and zero otherwise. The parentheses contain t-statistics computed from robust standard errors that correct for cross-sectional correlation in the data.

Intercept	8.31	(1.81)	8.36	(1.75)	8.40	(1.76)
D^{σ}	153.82	(31.55)	151.29	(27.52)	125.10	(21.22)
$(D^{\sigma})^2$			11.85	(5.87)		
$D^{\sigma,Open}$					30.57	(10.74)
$D^{\sigma} \times relOptVolume$	−2.58	(−1.38)	−2.00	(−1.06)	−1.46	(−0.77)
$D^{\sigma} \times histStockVol$	−0.48	(−0.55)	0.56	(0.61)	0.80	(0.89)
$D^{\sigma} \times \ln(size)$	−15.96	(−13.84)	−15.93	(−11.73)	−15.02	(−11.14)
$D^{\sigma} \times BM$	−3.85	(−0.72)	0.00	(5.20)	0.00	(5.01)
relOptVolume	−0.82	(−0.46)	−0.91	(−0.51)	−0.86	(−0.48)
histStockVol	−0.14	(−0.14)	−0.08	(−0.08)	−0.07	(−0.07)
ln(*size*)	−0.47	(−0.38)	−0.37	(−0.28)	−0.37	(−0.28)
BM	1.03	(0.21)	0.00	(0.08)	0.00	(0.08)
$D^{\sigma} \times Ind(EAD-5)$	23.02	(1.42)	23.85	(1.49)	22.27	(1.39)
$D^{\sigma} \times Ind(EAD-4)$	33.34	(2.25)	31.48	(2.11)	29.81	(2.00)
$D^{\sigma} \times Ind(EAD-3)$	22.56	(1.47)	28.66	(1.76)	25.92	(1.57)
$D^{\sigma} \times Ind(EAD-2)$	42.32	(2.77)	42.22	(2.76)	41.12	(2.70)
$D^{\sigma} \times Ind(EAD-1)$	62.89	(4.16)	63.19	(4.23)	61.35	(4.09)
$D^{\sigma} \times Ind(EAD-0)$	52.5	(3.90)	53.77	(4.00)	51.66	(3.85)
$D^{\sigma} \times Ind(EAD+1)$	26.94	(1.87)	29.75	(2.02)	29.33	(2.04)
$D^{\sigma} \times Ind(EAD+2)$	−11.37	(−1.04)	−9.72	(−0.87)	−9.07	(−0.83)
$D^{\sigma} \times Ind(EAD+3)$	−3.31	(−0.21)	1.14	(0.07)	−2.12	(−0.13)
$D^{\sigma} \times Ind(EAD+4)$	13.3	(0.60)	12.95	(0.58)	10.88	(0.49)
$D^{\sigma} \times Ind(EAD+5)$	−6.68	(−0.46)	−5.25	(−0.37)	−7.46	(−0.52)
$Ind(EAD-5)$	47.4	(4.24)	48.44	(4.33)	46.92	(4.21)
$Ind(EAD-4)$	32.8	(2.55)	33.09	(2.58)	31.53	(2.46)
$Ind(EAD-3)$	64.74	(5.32)	63.06	(5.12)	61.84	(5.02)
$Ind(EAD-2)$	85.31	(6.50)	85.40	(6.53)	84.63	(6.47)
$Ind(EAD-1)$	109	(9.01)	108.87	(9.04)	107.23	(8.91)
$Ind(EAD-0)$	−80.54	(−5.62)	−81.06	(−5.66)	−82.95	(−5.79)
$Ind(EAD+1)$	−338.91	(−23.03)	−342.80	(−23.17)	−343.42	(−23.35)
$Ind(EAD+2)$	−78.84	(−7.05)	−80.44	(−7.18)	−79.50	(−7.13)
$Ind(EAD+3)$	−63.84	(−5.72)	−64.02	(−5.76)	−63.72	(−5.77)
$Ind(EAD+4)$	−59.68	(−4.40)	−59.69	(−4.38)	−58.77	(−4.31)
$Ind(EAD+5)$	−48.86	(−4.52)	−49.17	(−4.54)	−49.58	(−4.60)
Adj. R^2	0.04		0.04		0.04	
Obs.	238,509		238,509		238,509	

coefficient estimates are close to monotonically increasing in the week leading up to the EAD, and the estimates for $n = -2$ and -1 are significant at conventional levels. These coefficient estimates indicate that as informational asymmetry increases in the days leading up to EADs, the price impact of a fixed quantity of volatility demand also increases. These results are consistent with market makers protecting themselves from greater concentrations of volatility information being brought to the option market as EADs approach. Indeed, the point estimate of 63 basis points for day -1 indicates that the price impact per unit of volatility demand increases by over 40% (= 62.89/153.82) from its baseline level just before EADs. This pattern of time variation in the price impact is a strong indication that informational asymmetry is an important component of the price impact captured in our paper. If the demand pressure were the main driving force, then we would not expect to observe this large variation in price impact.

As can be seen in Panel 3 of Figure 1, volatility demand pressure tends to be higher leading up to EADs. One might be concerned that the price impact of demand pressure is nonlinear with greater than linear increases in impact when volatility demand is high. To investigate this possibility, we add a squared volatility demand variable to the regression. The third and fourth columns of Table IX indicate that adding this variable to the regression results in hardly any change to the magnitude or significance of the coefficient estimates on the terms that interact demand for volatility with indicators of the number of trading days relative to an EAD.

The second approach to examining whether informational asymmetry plays a role in the price impact takes advantage of the fact that our data set distinguishes non-market maker volume that opens new option positions from non-market maker volume that closes existing positions. Indeed, as reported above in the predictive analysis, the volatility demand constructed from the open volume has a higher predictability than that from the close volume. For this reason, we included a second demand variable, $D^{\sigma,Open}$, in our price impact analysis. With the total demand variable in the same regression, the slope coefficient on $D^{\sigma,Open}$ effectively tests the differential price impact of the volatility demand constructed from open and close volume. Columns 5 and 6 of Table IX report that the coefficient estimate on this variable is positive and significant, indicating a greater price impact from the open volume demand. Clearly, pure demand pressure cannot explain this result. On the other hand, this empirical fact is consistent with the informational asymmetry explanation provided that market markers have some ability to distinguish open transactions from close transactions. Market makers are likely to develop some ability to distinguish between open and close volume in real time, because at the end of each trade day they can infer the net open and close volume on each contract from changes in open interest. Insofar as it is more difficult for them to develop this ability, it will bias against the positive and significant coefficient estimate that is observed.

Motivated by the same intuition, we also separate option volume by the moneyness of the option contract and construct the corresponding volatility demand variables. We find that the price impact per unit of net volatility demand is strongest for options that are very near the money, less strong but still appreciable for out-of-the-money options, and weaker but still significant for in-the-money options. These findings are not surprising, because near-the-money options have the greatest price sensitivity to volatility. Consequently, investors with volatility information are more likely to trade near-the-money options, and market makers adjust option prices most aggressively in response to near-the-money net demand for volatility.[20]

Finally, the control variables in Table IX include the indicator variables $Ind(EAD + n)$ to control for any overall changes in implied volatility around EADs that are not related to volatility demand. The large positive coefficient estimates on these indicator variables on days -2 and -1 and the negative coefficient estimates on days $+1$ and $+2$ relative to the EAD indicate that, not surprisingly, implied volatility rises before EADs and falls following them.

IV. Conclusion

Options play several important economic roles including that of providing a mechanism 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 whether option volume is informative about the future direction of underlying stock prices. However, while the option market is uniquely suited for trading on volatility information, there is little research on whether option volume is informative about the future volatility of underlying stocks.

This paper provides evidence that option volume is informative about future volatility by showing that non-market maker net demand for volatility in the option market is positively related to the subsequent realized volatility of underlying stocks, even after controlling for the public information about future volatility impounded in option-implied volatility. A natural interpretation of this finding is that investors choose to trade on private volatility information in the option market. This interpretation is supported by our findings that volatility demand from transactions that open new option positions is a stronger predictor of future volatility than demand that closes existing option positions and that demand from transactions that could have been part of straddle trades is a stronger predictor than demand that could not have been part of straddle trades.

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

[20] For the sake of brevity, we do not report these results. This finding also provides an interesting contrast to the findings for option trading on directional information. Black (1975) hypothesizes and Easley, O'Hara, and Srinivas (1998) show theoretically that investors with directional information on underlying stocks will use more highly out-of-the-money contracts to trade in the option market. Pan and Poteshman (2006) provide empirical support for these predictions.

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