

# **DETERMINANTS OF IMPLIED VOLATILITY SLOPE OF S&P 500 OPTIONS**

**by**

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## **Abstract**

We examine the possible determinants of the observed implied volatility skew of S&P 500 index options. We document that order flow toxicity measured by Volume-Synchronized Probability of Informed Trading (VPIN, Easley et al., 2012) is an important determinant of the slope of the volatility skew besides transactions costs and net buying pressure. We further analyze the relation at macroeconomic announcements and find that the effect of uncertainty resolution dominates when there is an announcement and when the surprise component of the announcement is higher. Model-free risk-neutral skewness measure which is highly correlated with slope is also significantly associated with VPIN.

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Implied volatility skew refers to the pattern where implied volatilities of at-the-money (ATM) options are lower than out-of-the-money (OTM) options. This empirical observation is an anomaly since the Black-Scholes Option Pricing Model presumes that for the same underlying asset, the implied volatilities shall be constant in the same maturity category across different strike prices. Recent research uses slope of implied volatility skew as a good proxy of ex-ante crash risk (Santa Clara and Yan 2010, Yan 2011). This paper examines the link between this important proxy and several market microstructure variables using high-frequency data for S&P 500 index options. We find that order flow toxicity measure of Easley, de Prado and O'Hara (2012) is one of the important determinants of the slope of the volatility skew besides transactions costs, and net buying pressure. Understanding the factors affecting implied volatility skew is important for the option pricing literature. The findings of this study are beneficial to option traders and financial analysts who closely monitor the volatility skew as they believe that it carries important information regarding the market structure and the risk aversion of market participants.

Alternative option pricing models attempt to account for the volatility skews by relaxing the distributional assumptions of the Black-Scholes model. However, none of the models provides a satisfactory explanation for this empirical irregularity. Given the limited success of these models, some researchers try to explain the economic determinants of the implied volatility function. Pena, Rubio and Serna (1999) is the first paper in that strain of literature and argue that transaction costs are the main determinants of the slope of the volatility skew of the Spanish Index Options. They also document that time to expiration and market uncertainty are important factors. Dumas, Fleming and Whaley (1998) suggest that past changes in

the index level and volatility surface may be related. Other researchers propose demand and supply based explanations to the volatility skews. For example, Bollen and Whaley (2004) suggest that the implied volatility skew of index options could be attributed to high demand from institutional investors for puts as portfolio insurance. Han (2008) takes a behavioral approach and relate implied volatility smile to investor sentiment. Liquidity is also reported as a factor that might affect the steepness of the implied volatility skew with mixed findings for different options.

The motivation of this study is to provide a better frame for the determinants of volatility skew of S&P 500 options in a high frequency setting. Besides variables that have shown to affect slope of implied volatility skew such as transaction costs and market uncertainty, we also investigate the effect of private information using a new metric, Volume Synchronized Probability of Informed Trading (VPIN) developed by Easley et al. (2012). This metric aims to measure order flow toxicity or adverse selection risk encountered by market makers in high frequency environments. VPIN is based on order imbalance and trade intensity in the market as informed traders are expected to trade on one side of the market and cause unbalanced volume. If market makers sense that order flow is toxic then they either cease or reduce their market making activities. In case they choose to continue to provide liquidity to the market, they charge higher prices for increased risk. Therefore we hypothesize that higher variability in slope of implied volatility skew will be observed with changes in VPIN level. We find that VPIN is a statistically significant factor that affects the shape of the volatility skews even after controlling for net buying pressure of Bollen and Whaley and other variables.

We then investigate the relation between the implied volatility skews and VPIN at macroeconomic announcement times. Macroeconomic announcements provide an avenue for investors to trade more aggressively on their private information (Pasquariello and Vega, 2007). In an earlier study, Admati and Pfleiderer (1988) document that informed traders try to time their trades at times of high level of trading and liquidity. We include 23 macro announcements in 2006. We also analyze the surprises contained in these announcements by computing the difference between the announced and expected figures. We find that uncertainty resolution affects slope at the time of macroeconomic announcements as well as when the surprise component is high.

Finally we conduct our analysis using risk-neutral skewness measure of Bakshi et al. (2003) which is highly correlated with slope. The beauty of this measure is that it is model-free and relies on the basic result that any payoff can be replicated and priced using options with different strikes (Bakshi and Madan, 2000). This purpose is to see whether the effect of order flow toxicity measured by VPIN metric is still strong when we use a model free proxy for risk aversion. Risk-neutral skewness deserves special attention since recent literature emphasizes a strong relation between an asset's risk-neutral skewness and future returns.

Our contribution can be summarized as follows. First, this paper analyzes possible determinants of slope of S&P 500 options in a high-frequency setting. Second, it uses a new proxy for the level of informed trading and order flow toxicity (VPIN) and shows that adverse selection risk significantly affects the shape of the volatility skews as well as risk neutral skewness besides time to maturity, transaction

costs and net buying pressure. Finally, the analysis differs from standard time based approaches and documents high-frequency behavior of slope in volume time i.e. sampling by using equal volume intervals.

The remainder of the paper is organized as follows. Section one discusses related literature. Section two describes the data and variable construction. Section three presents the results of the analysis of the determinants of implied volatility skews. In section four we look into VPIN and risk neutral skewness. Section five concludes the paper.

## **1. Literature Review**

The Black-Scholes Option Pricing Model presumes that for the same underlying asset, the implied volatilities shall be constant in the same maturity category across different strike prices. MacBeth and Merville (1979) and Rubinstein (1985) are the first papers to document that options on the same underlying with the same maturity dates have different implied volatilities across different strike prices. This anomaly is known as the volatility skew and takes the shape of a smile or a smirk depending on the instrument. Academicians investigate the possible reasons for this anomaly and the option pricing implications. Hull (1993) suggests that the empirical violations of the assumption of the normality of the log returns may cause this anomaly. One strand of literature has relaxed the distribution assumption of the Black-Scholes model (Heston, 1993; Bates, 1996), and incorporated stochastic volatility and jumps in option pricing models.

Other researchers use demand based arguments for option pricing and suggest that market participants' supply and demand for options is an important determinant in the pattern of implied volatilities. The argument is based on limits to arbitrage theorem: Market makers cannot afford to sell an infinite number of contracts for a specific option series. When demand for a specific series is high, market makers' portfolios become unbalanced and risky and they have to charge higher option prices. In this respect, excess demand (supply) for particular option series will cause implied volatility to increase (decrease). Bollen and Whaley (2004) show that net buying pressure for each option moneyness category significantly affects the shape of implied volatility function for S&P 500 index options<sup>4</sup>. Gârleanu et al's (2009) demand-based option model confirms prior results. They find that ATM options which have more than average implied volatility also have more than average demand.

Other papers take a different perspective and investigate possible determinants of implied volatility smile through cross-sectional analysis. In this literature, the purpose is to understand the dynamics and determinants of the volatility skew rather than to develop a new option pricing model. For example, Toft and Prucyk (1997) explain implied volatility skews by leverage and debt covenants for individual equity options. They find that the higher the firm leverage, the more pronounced the implied volatility skews. Moreover, the options on the firms that have stricter debt covenants

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<sup>4</sup> Bollen and Whaley (2004) note that there is considerable difference between trading volume and net buying pressure and these two are not necessarily highly correlated. For example trading volume may be high on days with significant information flow, but net buying pressure can be essentially zero if there are as many public orders to buy as to sell. They suggest the underlying reason why Dennis and Mayhew (2002) could not find any relation between risk neutral skewness and the ratio of average daily put volume to average daily call volume as a measure for public order is because trading volume is not a precise measure for net buying pressure. Moreover aggregate option volumes do not take into consideration option moneyness and both deep out-of-the-money and deep in-the-money puts are treated the same way.

also exhibit more pronounced volatility skews. Dennis and Mayhew (2002) investigate whether variables such as leverage, firm size, beta, trading volume, and/or the put/call volume ratio explain cross-sectional variations in risk neutral skewness measure of Bakshi, et al. (2003). Risk neutral skewness and kurtosis are closely related to the level and slope of implied volatility curve (Bakshi et al., 2003). Contrary to what Toft and Prucyk (1997) find, Dennis and Mayhew (2002) find the higher the leverage the less pronounced the volatility skews. They also document that larger firms with greater betas have more negative skews and firms with higher trading volume have more positive skews. Duan and Wei (2009) extend their study and argue that systematic risk is the driver for the observed pattern in implied volatility curve. After controlling for the overall level of total risk they find that for individual equity options, a steeper implied volatility curve is associated with a higher amount of systematic risk. From an accounting perspective, Kim and Zhang (2010) show that steepness of option-implied volatility smirks in individual equity options is significantly and positively related to financial reporting opacity. As seen from the above discussion, the evidence related to the determinants of volatility skew is mixed.

One line of literature suggests heterogeneous beliefs and investor sentiment to be a determining factor for the option implied volatility smile. One example is Buraschi and Jiltsov (2006) who develop an option pricing model where agents have heterogeneous beliefs on expected dividends. Han (2008) links implied volatility smile to investor sentiment. Liquidity is yet another factor that seems to affect the steepness of the implied volatility curve. Chou et al. (2009) report that the more liquid the option market, the steeper the volatility skews. Nordén and Xu (2012) find that options in different moneyness categories have significant differences in liquidity and

an improvement in the liquidity of an OTM put option relative to a concurrent ATM call option is found to lead to lower steepness. Deuskar et al. (2008) find a significant link between liquidity effect and the shape of the volatility skews only for long maturity options written on interest rates.

This study also contributes to the literature that investigates the determinants of jump risk. Yan (2011) argues that slope, defined as the difference between implied volatility of ATM puts and calls, measures the local steepness of the volatility skews and is a good proxy for jump risk. Understanding jump risk is important as Andersen Bollerslev and Diebold (2003) show that volatility estimates are more accurate when jumps are differentiated. Xing et al. (2010) suggest that volatility skews contains information related to jumps in at least three aspects: 1) the probability of a negative price jump 2) the expected size of the price jump 3) the jump risk premium that also compensates investors for the expected size of the jump. Cremers et al. (2008) show that volatility skews is a significant determinant of corporate credit spreads which are also highly sensitive to jump risk. Therefore, our study will also shed light on the possible determinants of the jumps in option prices.

This paper is also related to the literature that investigates the effects of macroeconomic news on financial markets. Ederington and Lee (1996) are the first to study the impact of news on option implied volatility. Kearney and Lombra (2004) find a significant positive relation between the CBOE volatility index, VIX, and unanticipated changes in employment, but not inflation. Andersen et al. (2007), investigate the impact of public news on returns and volatility in three markets: foreign exchange, bond and equity markets using high-frequency intraday data. They find that macro announcement surprises significantly affect the returns and volatilities

in all three markets. Onan et al. (2014) associate high-frequency changes in VIX and slope with macroeconomic announcements. Different from other studies, this paper looks at the impact of VPIN and other potential factors on slope at macroeconomic announcement times.

## 2. Data and Variable Construction

The purpose of this section is to describe the data, volume time approach and the variables that we use as possible determinants of slope of implied volatility skew of S&P 500 Index Options.

### 2.1 Data

The data consists of tick-by-tick data of S&P 500 Index (SPX) option contracts and is obtained from Berkeley Options Database for a total of 251 trading days in 2006<sup>5</sup>. The dataset is derived from the Market Data Report (MDR file) of the Chicago Board Options Exchange (CBOE) and includes time-stamped (in seconds) option trades and quotes (options of all strikes and maturities) including expiration date, put – call code, exercise price, bid and ask prices and contemporaneous price of the underlying S&P 500 Index. Daily S&P 500 continuous dividend yields are obtained from the DataStream database.

Tick by tick options data is filtered based on maturity, no-arbitrage lower option boundaries and for obvious reporting errors and outliers. In order to avoid

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<sup>5</sup> Sample data does not coincide with US financial crisis of 2007-2009.

implied volatilities that are likely to be measured with error, only options with bid prices greater than zero are used<sup>6</sup>. Put-Call parity violations are not filtered as they might contain evidence related to the trading activity of informed traders (Cremers and Weinbaum, 2010). We include options that have maturities between 15 and 45 trading days since these are the most liquid options. This study does not include options that have maturities shorter than 15 days, as shorter term options have relatively small time premiums and are substantially unreliable when calculating option implied volatilities (Dumas et. al., 1998).

Trading hours on the CBOE begin at 8:30 a.m. (CST) and end at 3:15 p.m. (CST); however, New York Stock Exchange (NYSE) closes at 4:00 p.m. (EST) and this corresponds to 3:00 p.m. (CST). Therefore, we delete all option quotes after 3:00 p.m. (CST) in order not to have non-synchronicity problem in our analysis. We plot the intraday behavior of trading activity in Figure 1. We observe that the average number of contracts traded and dollar volume are highest within the first trading hour. Average number of contracts then gradually decreases till noon and slightly increases towards closing. Average volume makes a peak in the early afternoon between 12:30 to 13:30 and towards closing around 15:00. The observed patterns could be attributed to the macroeconomic announcement timings at 8:30 EST and market opening effects.

.....Insert Figure 1 about here.....

One of the problems of working with high frequency data is arrival of market ticks at random time. Regular time-series econometric tools which frequently use backward operators cannot be applied to irregularly spaced or nonhomogeneous time

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<sup>6</sup> In a same manner, but a bit different approach, some authors use options with bid-ask midpoints higher than 0.125 or 0.25.

series (Gencay et al., 2001). Traditional approach to this problem is to equally space time-series data and work with time bars. Alternative approach to working with nonhomogeneous data is to use volume bars. Every time a predetermined level of volume is traded in the market marks the separation of volume bars. In this study, we employ volume bars for analysis or in other words work in volume time. Easley et al. (2012) argue that in a high frequency framework, volume time, measured by volume increments, is a more relevant metric compared to clock time as trades take place in milliseconds.

Following Easley et al (2012), we group sequential trades in the so-called volume buckets until their combined volume equals constant size,  $V$ , which is an exogenously defined fixed size. In the analysis, we define  $V$  as one thirteenth of the average daily volume. If the size of the last trade that is needed to complete a bucket is greater than needed, then excess part of that trade is assigned to the next bucket. The time needed to fill a bucket is related to the existence of amount of information. Easley and O'Hara (1992) suggest that the time between trades is correlated with the presence of new information. Therefore if a very relevant piece of news arrives to the market, we may expect to see a lot of activity in the market and volume buckets filling up quickly. Hence, volume time is updated in stochastic time matching the arrival rate of information. Easley et al. (2012) argue that equal volume intervals stand for comparable amount of information.

## 2.2 Variable Construction

### 2.2.1 Slope

We first group options in moneyness categories according to their deltas as in Bollen and Whaley (2004). Besides forward price of the underlying asset, an option's moneyness also depends on volatility of the underlying asset and time to maturity of the option and delta accounts for these two factors. Table I lists the upper and lower boundaries of moneyness categories. Options with absolute deltas below 0.02 or above 0.98 are excluded to avoid price distortions.

.....Insert Table I about here.....

We calculate implied volatilities of the European-style S&P 500 index options for each moneyness category using the extension of Black and Scholes (1973) option pricing formula that incorporates continuous dividends. To proxy risk-free rate, we calculate implied risk-free rate from put-call parity relations of options written on S&P 500 Index. Daily SPX dividend yields obtained from the DataStream are used in implied volatility calculations.

We first calculate implied volatility for each trade in a volume bucket, then average these implied volatilities for each moneyness category. We then calculate two measures of slope taking differences of average implied volatilities as follows:

$$\text{Slope}_1 = IV_{ATMP} - IV_{ATMC} \quad (1)$$

$$\text{Slope}_2 = IV_{OTMP} - IV_{ATMC}$$

where  $IV_{ATMP}$  and  $IV_{OTMP}$  are implied volatilities of ATM and OTM puts respectively and  $IV_{ATMC}$  is implied volatility of ATM calls. Figure 2 graphs the average implied volatilities of all traded call and put options in 2006 as a function of moneyness level. The average of the volatility skews has a smirk shape during 2006 in line with

previously documented patterns. As observed in the figure average implied volatility of put options is higher than that of call options. This is intuitive as put options are demanded and traded more.

.....Insert Figure 2 about here.....

### **2.2.2 Liquidity and Transaction Costs**

There are numerous studies on the effects of liquidity on stock market, but research is limited for the derivatives market. Moreover, the effect of liquidity on option prices is not easy to interpret as investors hold both short and long positions. In an option pricing model, Cetin et al. (2007) model liquidity costs as a stochastic supply curve with the underlying asset price depending on order flow and suggest that liquidity costs may be partially responsible for the implied volatility “smile”. Chou et al. (2011) show that liquidity affects both the level and slope of implied volatility curve for 30 component stocks in the Dow Jones Industrial Average (DJIA). Specifically they find that when the option market is more liquid (lower bid-ask spreads for options), the implied volatility curve is steeper. Deuskar, et al. (2011) use bid-ask spreads to proxy for illiquidity and find that illiquid interest rate options trade at higher prices relative to more liquid options in the over-the-counter market. Feng et al. (2014) provide evidence supporting the notion that option pricing models must incorporate liquidity risks. In this respect, we try to control effects of liquidity in our sample by choosing short-term options which are most liquid. Moreover, sampling by equal volume buckets also helps us to control for liquidity effects since a widely used measure of liquidity in options market is the log of number of option contracts for an interval and volume buckets include same fixed number of contracts.

Using daily S&P 100 Index option prices, Longstaff (1995) shows that market frictions such as transaction costs also play a major role on option prices besides market illiquidity. Pena et al. (1999) find that transactions costs estimated by daily average relative bid-ask spread of options, significantly affect the shape of the implied volatility functions. Ederington and Guan (2002) also present evidence that transaction costs related to the construction of the delta neutral portfolio cause volatility smiles. As a proxy for transaction costs, for each transacted option, we calculate a relative bid-ask spread, namely bid-ask spread divided by an option's mid quote as in Amihud and Mendelson (1986). We then calculate an average relative bid-ask spread for each moneyness category in a volume bucket. Relative bid-ask spread is also considered a good proxy for liquidity.

### **2.2.3 Momentum**

According to market momentum hypothesis, if past returns are positive, investors expect future stock returns to be positive and they will tend to buy call options on the market index. Similarly, if past returns are negative, investors will buy put options. High demand for call (put) options will create an upward pressure on call (put) prices. Pena et al. (1999) find that market momentum is a determinant for the level of implied volatility function for Spanish IBEX-35 Index options. They proxy momentum with log of the ratio of the three-month moving average of value weighted IBEX to its current level. Amin et al. (2004) also find that option prices depend on stock market momentum. They observe that when stock returns decline, call-smile more than doubles and put smile more than triples. The effect is visible for at-the-

money options but higher for out-of-the money options. They conclude that even though market momentum seems to affect the volatility smiles, it does not completely explain volatility smiles. We include momentum in our set of explanatory variables and calculate daily index return on a rolling window basis using thirteen volume buckets.

#### **2.2.4 Time to maturity and market uncertainty**

Pena et al. (1999) find that option's time-to-expiration and market uncertainty are also important variables that explain the smile of implied volatility function of Spanish IBEX-35 Index options. In this respect, we include time to maturity as an explanatory variable since volatility skew of S&P 500 Index options may also be changing throughout option's life. Option's time to maturity is the annualized number of calendar days between the trade date and the expiration date. Another variable we include in the analysis is market uncertainty about the return of S&P 500 Index and we proxy it with daily realized volatility which is the sum of squared five-min returns during each day (Andersen et al., 2001). Alternatively we use VIX as a proxy for market uncertainty<sup>7</sup>.

#### **2.2.5 Net Buying Pressure**

Bollen and Whaley (2004) define Net Buying Pressure (NBP) as the difference between the number of buyer-motivated contracts and the number of seller-motivated contracts traded and show that NBP, especially for index puts, affect shape and movement of implied volatility function for S&P 500 index options. They calculate

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<sup>7</sup> Results are very similar.

NBP daily for each options series, multiply it by the absolute value of the option's delta and standardize it with volume. In a similar fashion, we calculate NBP for each moneyness category in a volume bucket and include it in our analysis with other possible determinants of slope of implied volatility skew of S&P 500 options.

In order to calculate NBP, we first need to know which trades are buyer motivated and which trades are seller motivated. We apply widely used Lee and Ready (1991) algorithm to classify trades. According to this algorithm, transactions that occur at prices higher (lower) than the quote midpoint are classified as buyer-initiated (seller-initiated). Transactions that occur at a price that equals the quote midpoint but is higher (lower) than the previous transaction price are classified as buyer-initiated (seller-initiated). Transactions that occur at a price that equals both the quote midpoint and the previous transaction price but is higher (lower) than the last different transaction price are classified as being buyer-initiated (seller-initiated). Table II shows the distribution of buyer and seller motivated trades in our sample. 53.2% of transactions are buys and 45.5% are sells. We discard unidentified trades which constitute 1.3% of the sample.

.....Insert Table II about here.....

Once we have identified buyer and seller motivated trades, we calculate NBP using aggregate volume of all options as well as using volume of call and put option series separately. As defined previously, NBP is the difference between buyer motivated and seller motivated trades. We calculate NBP for each moneyness category in a volume bucket. Table III shows NBP for S&P 500 Index options in our filtered sample in terms of moneyness category. In line with prior evidence, put

option trading is much higher than index call option trading. We observe that trading is mainly concentrated on ATM, OTM and DOTM options.

.....Insert Table III about here.....

### **2.2.6 Volume-Synchronized Probability of Informed Trading (VPIN)**

We further investigate the role of demand and supply for different option series on slope of implied volatility skew. Since level of private information and adverse selection risk are key factors for market makers' portfolio rebalancing and supply, a metric that measures these may be an important determinant of implied volatility skew. We use a new metric, VPIN, introduced by Easley et al (2012), to assess the level of informed trading and adverse selection risk of market makers. Informed trading for index options may arise if investors learn anything related to the macroeconomic announcements before the release time. Bernile et al. (2014) find evidence that there is information leakage especially ahead of the Federal Open Market Committee (FOMC) monetary policy announcements. Private information may also arise from heterogeneous interpretations of public information (Green, 2004). Investors who are credited with superior analytical skills or who are using superior models are likely to better process information. Private information for stock index options arises, because, even though everybody sees the same set of public news, their interpretation of the news may differ. A public news event can cause buy and sell decisions at the same time if investors use different models and disagree about the interpretation of the news. Kandel and Pearson (1995) also provide empirical evidence against the assumption that agents interpret public information identically.

VPIN measures the level of informed trading or the so-called order flow toxicity based on order imbalance and trade intensity in the market. Toxicity refers to the adverse selection risk of market makers and uninformed investors or risk of loss in trading with better informed parties. Informed traders are expected to trade on one side of the market and cause unbalanced volume. If market makers sense that order flow is toxic then they either cease or reduce their market making activities. In case they choose to continue to provide liquidity to the market, they charge higher prices for increased risk. Therefore, we hypothesize that there will be higher variability in prices and movement in slope, associated with increases in VPIN.

VPIN is based on the imbalance between buy and sell orders for each volume bucket during a sample window for all traded options. If we let  $\tau = 1, \dots, n$  be the index of equal volume buckets, then a VPIN value for each volume bucket is calculated as follows:

$$VPIN \approx \frac{\sum_{\tau=1}^n |V_{\tau}^S - V_{\tau}^B|}{nV} \quad (2)$$

where  $V$  is the constant bucket size and equal to  $1/13^{\text{th}}$  of the average daily volume in our sample,  $V_{\tau}$  are the equal volume buckets for  $\tau = 1, \dots, 13$  per day,  $V_{\tau}^S$  is the volume classified as sell,  $V_{\tau}^B$  is the volume classified as buy, and ‘ $n$ ’ is length of the sample window or the number of buckets used to approximate the expected trade imbalance and intensity. VPIN is estimated on a rolling basis. This rolling calculation makes VPIN highly auto correlated but dropping buckets along the calculation avoids long memory in the process. If we let rolling window sample size  $n$  to be 5, then when sixth bucket is filled, bucket one is dropped and the new VPIN metric is calculated based on bucket two through six. VPIN value of the 6th bucket is independent from

the VPIN value of the first bucket. If we let  $n$  to be 13, then this is equivalent to calculating a daily VPIN. Since we are working with high frequency data we want VPIN metric to be updated intraday and we use  $n$  as 5. We have an average of 13 VPIN values per day but on very active days the VPIN metric is updated much more frequently than on less active days.

VPIN has two advantages compared to PIN measure (Easley et al., 1996) which has been widely used in the literature as a proxy for the level of informed trading in markets. First, we do not have to estimate unobserved parameters for VPIN. Second, there are also criticisms against PIN for being a proxy for only illiquidity effects and not asymmetric information. (Duarte and Young, 2009; Akay et al., 2012). VPIN is less prone to infrequent trading since equal volume buckets are used. Table IV presents the summary statistics for our variables in volume time. Average VPIN is 0.38 with a maximum of 1 and a minimum of 0.04. Average implied volatility is 10% for calls and 17% for puts. Average VIX is 13.09% annually.

.....Insert Table IV about here.....

### **3. Empirical Results**

The objective of this section is to explore the linkage between the variables discussed in the prior section and changes in slope of implied volatility skew of S&P 500 options. We start the analysis by conducting the Augmented Dickey-Fuller stationarity tests on our variables. We are able to reject the existence of a unit root for all of our variables and first difference of VIX. Observation of the ACF reveals that

change in slope is highly auto-correlated and we include first lag of slope as an independent variable in the regression.

To assess the relation between slope and variables discussed above, we estimate the following regression with Newey-West corrected standard errors:

$$\Delta Slope_n = \alpha + \beta_1 \Delta Slope_{n-1} + \beta_2 R_n + \beta_3 Time_n + \beta_4 Spread_n + \beta_5 RV_n + \beta_6 NBP_n + \beta_7 VPIN_n + e_n \quad (3)$$

where  $\Delta Slope_n$  is change in one of the two measures of slope defined in Equation (1) from volume bar  $n-1$  to  $n$ .  $R_n$  is the index return computed from volume bar  $n-13$  to  $n-1$  for the momentum effect.  $Time_n$  is option's annualized time to maturity.  $Spread_n$  is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and is calculated for calls and puts separately for each moneyness category.  $RV_n$  is realized volatility which is the sum of squared five-min returns during each day.  $NBP_n$  is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta for each moneyness category of calls and puts separately. NBP variables vary in different regressions depending on the slope measure.  $VPIN_n$  is the metric for probability of informed trading and calculated as in Equation (2).

Table V displays the results of regression in Equation (3) and show that all of our variables except momentum seem to contribute to the variability of slope of implied volatility skew of S&P 500 Index Options. Pena et al. finds a weak relation between market momentum and degree of curvature of the smile and in our analysis the effect of momentum on slope is not significant. In line with Pena et al.'s (1999) findings for Spanish Index options we find that change in slope of S&P 500 Index options is related to transactions costs represented by bid-ask spreads and option time

to maturity. The lagged change in slope is negatively and significantly related to current change in both measures of slope. This is in line with limits to arbitrage theorem which suggests that as market makers rebalance their portfolios, prices reverse to their previous levels gradually.

In line with Bollen and Whaley (2004), NBP of options significantly affect slope. NBP of ATM calls seem to be negatively associated with both measures of slope. NBP of ATM (OTM) puts is significantly and positively associated with Slope<sub>1</sub> (Slope<sub>2</sub>). Besides these variables, we find a significant relation between VPIN and slope. The relation is positive for both measures of slope. This implies that the higher the level of private information and order flow toxicity in the market, the more asymmetrically the OTM and ATM puts are valued in the market relative to ATM calls.

.....Insert Table V about here.....

Informed traders try to time their trades at times of high level of trading and liquidity and macroeconomic announcements provide an avenue for investors to trade more aggressively on their private information. If VPIN captures the probability of informed trading well, then it would be interesting to see the relation between VPIN and slope at macroeconomic announcement times. The macroeconomic announcement timings, realizations and survey expectations are obtained from Bloomberg. Table VI lists the macroeconomic announcements that we include in our analysis. We include 23 macroeconomic announcements and most of the announcements are monthly but initial jobless claims announcement is weekly and we also have a number of quarterly announcements.

.....Insert Table VI about here.....

We first visually examine behavior of slope and VPIN around macroeconomic announcements. We calculate the averages of slope and VPIN for each volume bar corresponding to the announcement time  $t$ , and up to 15 pre-announcement and post-announcement volume bars from January through December in 2006. Figures 3 and 4 plot these averages. Figure 3 shows that  $\text{Slope}_2$  drops sharply in response to an announcement release but drop is not that significant for  $\text{Slope}_1$ . In Figure 4, we observe that VPIN calculated over a window size of 5, starts to decrease 5 volume bars before the announcement and increases afterwards. Before the announcement, we observe a tranquil period for informed traders in options market, which could be due to investors' tendency to wait for the releases and postpone their trades. Informed trading activity increases within nine volume bars following an announcement. As most of the announcements coincide with market opening, it is difficult to anticipate the response time of the informed traders to the announcement release, nine volume bars might correspond to a very short period of response time.

.....Insert Figure 3 and 4 about here.....

We continue our analysis with adding one more variable to the regression equation (3) to test the relation between VPIN and implied volatility skew at macroeconomic announcements times. This variable is the News dummy which is 1 if there is a macroeconomic announcement and 0 otherwise. Table VII summarizes the results. When we account for macroeconomic announcements, the effect of VPIN is less significant for both  $\text{Slope}_1$  and  $\text{Slope}_2$ . We observe a strong negative impact of News dummy on  $\text{Slope}_2$ . This suggests that the effect of uncertainty resolution

dominates when there is a macroeconomic announcement and OTM puts are valued more symmetrically in the market relative to ATM calls. This is also observed in Figure 3 as a sharp drop in Slope<sub>2</sub>.

.....Insert Table VII about here.....

Next we look into the surprise component of the announcement and analyze whether there is a stronger impact on slope when the surprise is bigger. The surprise component is defined as the difference between the announced figure and survey expectations. Surprises are assumed to be stochastic since they are related to the incorrect anticipation by the market participants. To allow for meaningful comparisons of coefficients across different announcements, we standardize news by the standard deviation of the surprise component for different announcements as in Andersen et al. (2003, 2007). The standardized news for announcement k at time t,  $Surprise_{k,t}$ , is defined as follows:

$$Surprise_{k,t} = \frac{Actual_{k,t} - Expectation_{k,t}}{\hat{\sigma}_k} \quad (4)$$

where  $Actual_{k,t}$  refers to the announced value and  $Expectation_{k,t}$  refers to the market's expectation, for macro fundamental k at time t.  $\hat{\sigma}_k$  refers to the sample standard deviation of the surprise component, the difference between  $Actual_{k,t}$  and  $Expectation_{k,t}$  is constant for any macro fundamental k. Table VIII reports the results of the regression Equation (3) with additional two variables which are  $Surprise_{k,t}$ , as defined in Equation (4) and an interaction term of  $Surprise_{k,t}$  with  $VPIN_n$ . We observe that results are not much different from table VII. The effect of uncertainty resolution

is still there for Slope<sub>2</sub> and the impact of the macroeconomic surprises are not higher than the impact of macroeconomic announcement dummy variable.

.....Insert Table VIII about here.....

#### 4. Risk Neutral Skewness and VPIN

In this section we further investigate whether order flow toxicity measured by VPIN metric is associated with risk aversion. As a proxy for risk aversion, we use risk-neutral skewness measure of Bakshi et al. (2003). The beauty of this measure is that it is model-free and relies on the basic result that any payoff can be replicated and priced using options with different strikes (Bakshi and Madan, 2000). Bakshi et al. (2003) show that the more negative the risk-neutral skew, the steeper the volatility smile is. In this respect, we expect variability of VPIN to be associated with higher variability in risk-neutral skewness as well.

Risk neutral skewness and kurtosis are recovered using market prices of OTM calls and puts as follows:

$$SKEW(t, \tau) = \frac{e^{r\tau}W(t, \tau) - 3e^{r\tau}\mu(t, \tau)V(t, \tau) + 2\mu(t, \tau)^3}{[e^{r\tau}V(t, \tau) - \mu(t, \tau)^2]^{3/2}} \quad (5)$$

$$KURT(t, \tau) = \frac{e^{r\tau}X(t, \tau) - 4e^{r\tau}\mu(t, \tau)W(t, \tau) + 6e^{r\tau}\mu(t, \tau)^2V(t, \tau) - 3\mu(t, \tau)^4}{[e^{r\tau}V(t, \tau) - \mu(t, \tau)^2]^2}$$

Where  $C(t, \tau; K)$  and  $P(t, \tau; K)$  are the prices of index calls and puts with strike price, K, and expiration  $\tau$  periods from time t.  $u(t, \tau)$  and the prices of quadratic, cubic and quartic contracts are as follows:

$$u(t, \tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V(t, \tau) - \frac{e^{r\tau}}{6} W(t, \tau) - \frac{e^{r\tau}}{24} X(t, \tau) \quad (6)$$

$$V(t, \tau) = \int_{S(t)}^{\infty} \frac{2 \left( 1 - \ln \left( \frac{k}{S(t)} \right) \right)}{K^2} C(t, \tau; K) dK$$

$$+ \int_0^{S(t)} \frac{2(1 + \ln \left( \frac{k}{S(t)} \right))}{K^2} P(t, \tau; K) dK$$

$$W(t, \tau) = \int_{S(t)}^{\infty} \frac{6 \ln \left( \frac{k}{S(t)} \right) - 3 \ln \left( \frac{k}{S(t)} \right)^2}{K^2} C(t, \tau; K) dK$$

$$- \int_0^{S(t)} \frac{6 \ln \left( \frac{k}{S(t)} \right) + 3 \ln \left( \frac{k}{S(t)} \right)^2}{K^2} P(t, \tau; K) dK$$

$$X(t, \tau) = \int_{S(t)}^{\infty} \frac{12 \ln \left( \frac{k}{S(t)} \right)^2 - 4 \ln \left( \frac{k}{S(t)} \right)^3}{K^2} C(t, \tau; K) dK$$

$$- \int_0^{S(t)} \frac{12 \ln \left( \frac{k}{S(t)} \right)^2 + 4 \ln \left( \frac{k}{S(t)} \right)^3}{K^2} P(t, \tau; K) dK$$

We use trapezoid estimations to calculate the above integrals as in Dennis and Mayhew (2002) and Conrad et al. (2013) and estimate moments for each volume bucket in our sample.

We then investigate whether VPIN is associated with risk neutral skews using our prior ordinary least squares regression using change in skewness as the dependent variable and including kurtosis as an additional control variable.

$$\Delta Skew_n = \alpha + \beta_1 Kurt_n + \beta_2 R_n + \beta_3 Time_n + \beta_4 Spread_n + \beta_5 RV_n + \beta_6 NBP_n + \beta_7 VPIN_n + e_n$$

where  $\Delta Skew_n$  is change in skewness and  $Kurt_n$  is defined in Equation (5) and all the other variables are defined as before. Table IX presents the regression results. We observe that among all the factors, time-to-maturity and VPIN are the ones that are significantly associated with changes in risk-neutral skewness. In line with our expectations there is a positive relation between VPIN and change in skewness. This suggests that at high levels of order flow toxicity, market risk aversion changes as well. This finding serves as a robustness check for the significant positive relation we find between change in slope and VPIN as we did not depend on any model when we calculated risk neutral skewness.

## 5. Conclusion

This paper examines the high frequency characteristics of S&P 500 index options' implied volatility skew. Slope of implied volatility skew is a good proxy for jump risk and investor risk aversion. In an attempt to explain changes in implied volatility skew, we examine a range of microstructure variables including the level of market order flow toxicity proxied by VPIN metric. Our analysis is carried out in equal volume bars that match the arrival rate of information to the market. Results document a statistically significant relation between slope and order flow toxicity even after controlling for liquidity, volatility and momentum effects, transaction costs and net buying pressure. In this respect, option pricing models may benefit from incorporating a measure of market makers' adverse selection risk.

We further analyze the relation between VPIN and slope at macroeconomic announcement times. Informed traders try to time their trades at times of high level of trading and liquidity and macroeconomic announcements provide an avenue for investors to trade more aggressively on their private information. We find that when there is a macroeconomic announcement, the association between VPIN and both measures of slope is weaker. When there is a macroeconomic announcement, the effect of uncertainty resolution seems to dominate and OTM puts are valued more symmetrically in the market relative to ATM calls.

Finally we investigate whether order flow toxicity measured by VPIN metric is associated with risk-neutral skewness which is highly correlated with slope. Risk neutral skewness measure of Bakshi et al. (2003) is model-free and uses prices of options with different strikes. We expect to see a significant relation between risk neutral skewness and VPIN. In line with our expectations, we observe that order flow toxicity and level of private information is significantly associated with investor risk aversion proxied by risk-neutral skewness. A clearer comprehension about the factors that affect the slope and risk-neutral skewness is important for developing new option pricing models and devising proper hedging and investment strategies. Our results justify why traders shall closely monitor slope and skewness to understand how jump risk and risk aversion are evolving during a trading day.

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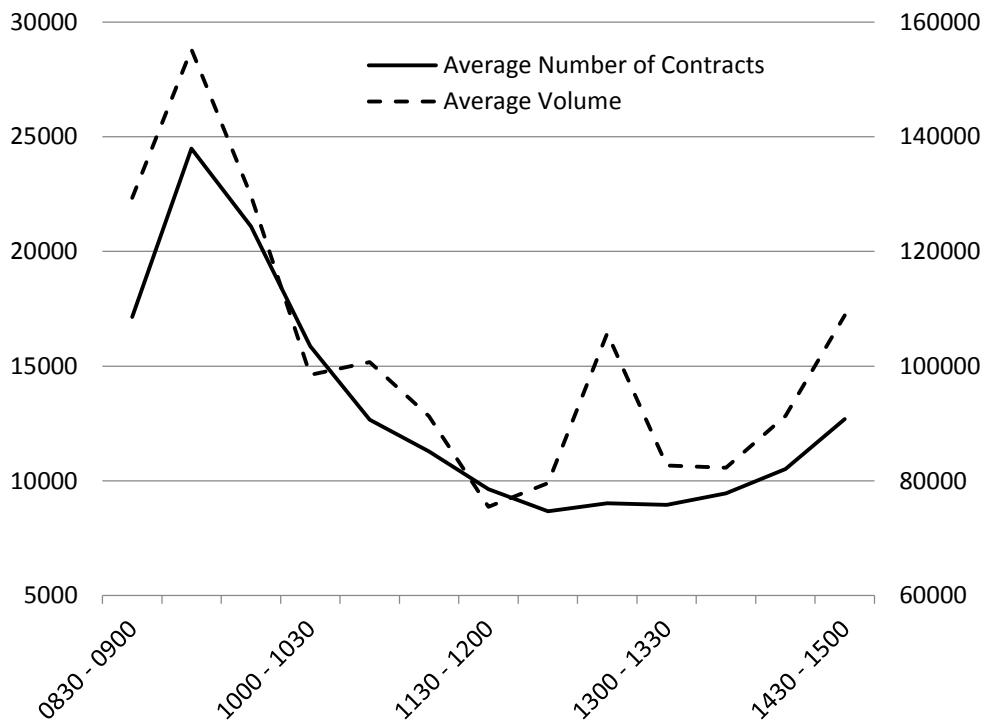
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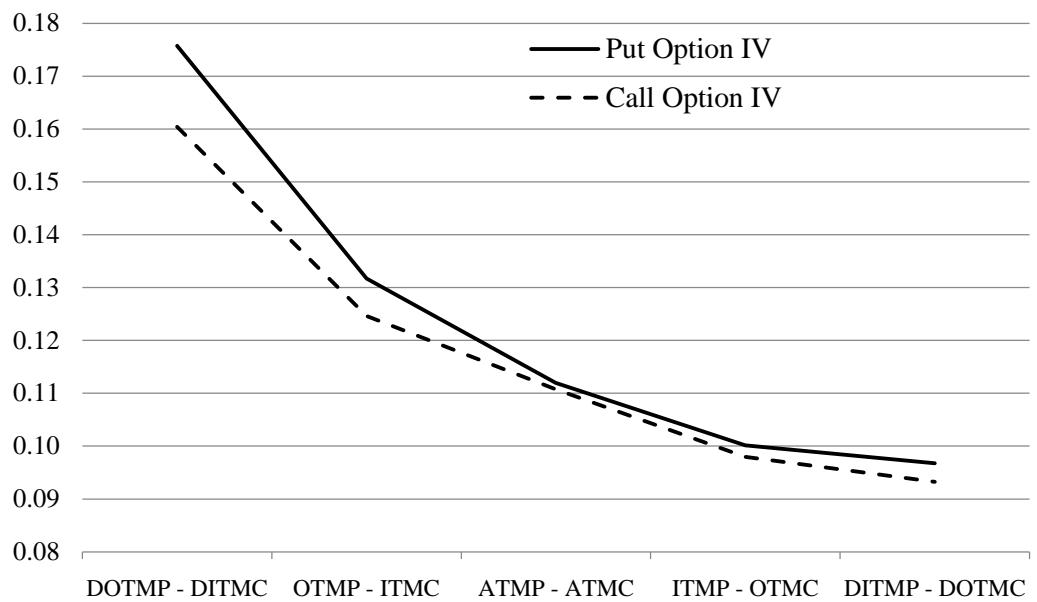
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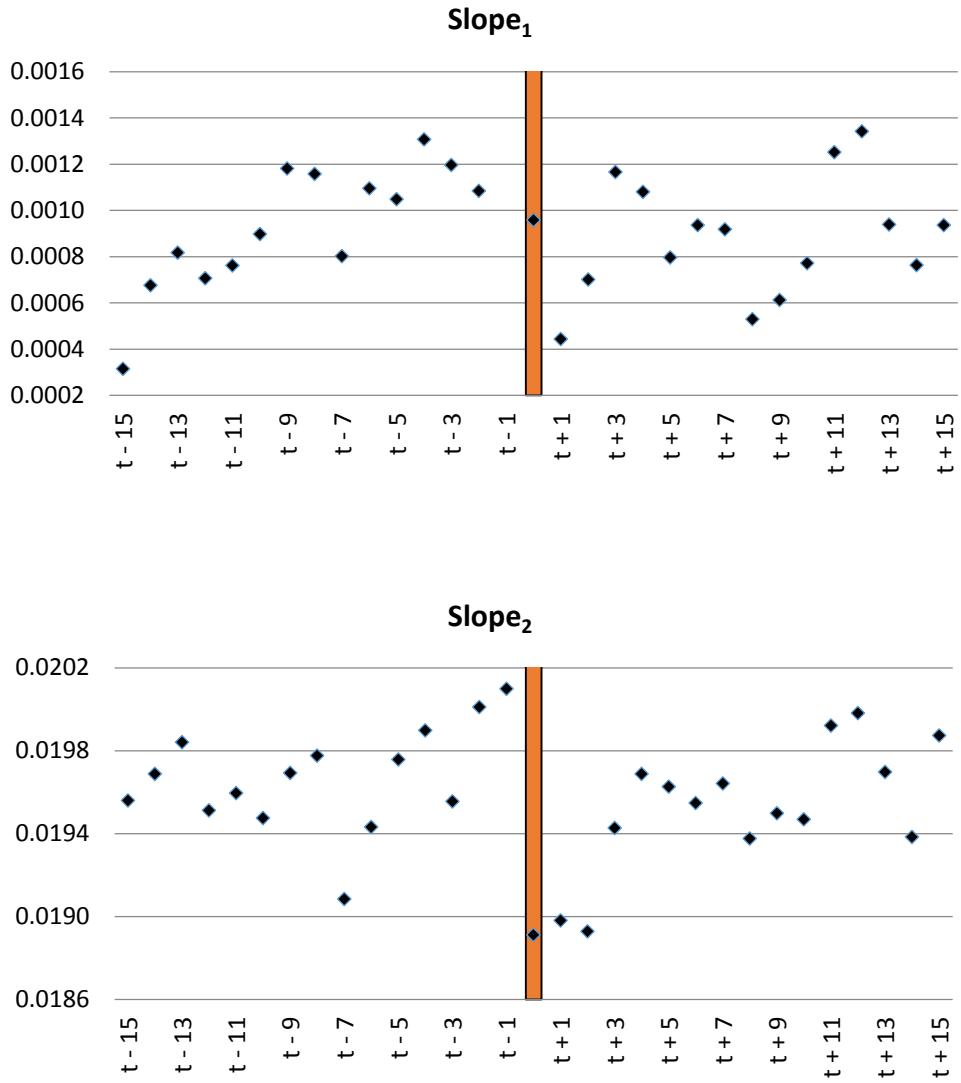
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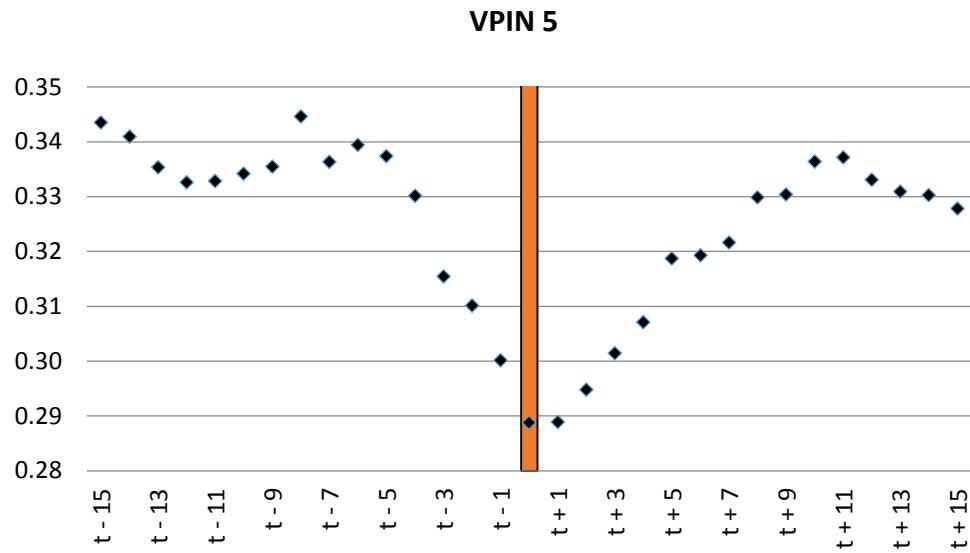
**Figure 1: Intraday behavior of S&P 500 trading** Figure shows the intraday (thirty-min) behavior of average number of contracts and average dollar volume for SPX thirty-day options for a total observations of 585,991 during 2006.



**Figure 2. Option Implied Volatilities.** Figure plots the average implied volatilities of call and put options as a function of moneyness for the SPX Options during 2006 using high frequency data.



**Figure 3. Behavior of Slope at Announcements in Volume Time.** Figure plots the average of slope for each volume bucket corresponding to the announcement time  $t$  during 2006. Pre-announcement and post-announcement means of slope are also included up to 15 volume buckets



**Figure 4. Behavior of VPIN at Announcements in Volume Time.** Figure plots average of VPINs for each volume bucket corresponding to the announcement time  $t$  during 2006. Pre-announcement and post-announcement means of VPIN are also included up to 15 volume buckets. Length of the sample window that VPIN is updated on a rolling basis is 5.

**Table I****Moneyness Category Definitions of S&P 500 Index Options**

Table presents delta upper and lower bounds of the moneyness categories of S&P 500 Index Options. Options with absolute deltas below 0,02 and above 0,98 are excluded.

<b>Option Category</b>	<b>Call Option Delta Lower Bound</b>	<b>Call Option Delta Upper Bound</b>
DITMC - Deep in the money call option	0,875	0,98
ITMC - In the money call option	0,625	0,875
ATMC - At the money call option	0,375	0,625
OTMC - Out of the money call option	0,125	0,375
DOTMC - Deep out of the money call option	0,02	0,125
<b>Option Category</b>	<b>Put Option Delta Lower Bound</b>	<b>Put Option Delta Upper Bound</b>
DITMP - Deep in the money put option	- 0,98	- 0,875
ITMP - In the money put option	- 0,875	- 0,625
ATMP - At the money put option	- 0,625	- 0,375
OTMP - Out of the money put option	- 0,375	- 0,125
DOTMP - Deep out of the money put option	- 0,125	- 0,02

**Table II**  
**Distribution of Buyer/Seller Motivated S&P 500 Index Option Trades**

Table presents the distribution of buyer/seller motivated S&P 500 Index options traded on Chicago Board Options Exchange in 2006 subject to filtration discussed in section 2.1. We use Lee and Ready (1991) algorithm to classify trades. According to this algorithm, transactions that occur at prices higher (lower) than the quote midpoint are classified as buyer-initiated (seller-initiated). Transactions that occur at a price that equals the quote midpoint but is higher (lower) than the previous transaction price are classified as buyer-initiated (seller-initiated). Transactions that occur at a price that equals both the quote midpoint and the previous transaction price but is higher (lower) than the last different transaction price are classified as being buyer-initiated (seller-initiated). We discard unidentified trades which constitute 1.3% of the population.

<b>Identification Type</b>	<b>Number of Trades</b>	<b>Prop. of Total</b>
Buy	256,332	53.2%
Sell	219,081	45.5%
Unidentified	6,317	1.3%
Total	481,730	100.0%

**Table III**  
**Summary of Net Buying Pressure for S&P 500 Index Options**

Table presents the distribution of buyer/seller motivated S&P 500 Index options, traded on Chicago Board Options Exchange in 2006 subject to filtration discussed in section 2.1, according to moneyness categories. Moneyness category definitions are as in Table I. *Net* is the difference between buyer and seller motivated trades.

	Category	Buy	Sell	Net	Total	Prop. of Total (%)
<b>CALLS</b>	DITMC	195,785	114,15	81,635	309,935	0.7
	ITMC	543,831	543,418	413	1,087,249	2.5
	ATMC	2,446,186	2,249,534	196,652	4,695,720	10.9
	OTMC	2,010,184	1,632,883	377,301	3,643,067	8.5
	DOTMC	2,576,943	2,593,281	-16,338	5,170,224	12.0
	<b>TOTAL</b>	<b>7,772,929</b>	<b>7,133,266</b>	<b>639,663</b>	<b>14,906,195</b>	<b>34.7</b>
<b>PUTS</b>	DITMP	48,866	15,012	33,854	63,878	0.1
	ITMP	167,299	213,136	-45,837	380,435	0.9
	ATMP	2,383,708	2,229,217	154,491	4,612,925	10.7
	OTMP	3,899,926	3,492,139	407,787	7,392,065	17.2
	DOTMP	7,782,305	7,810,069	-27,764	15,592,374	36.3
	<b>TOTAL</b>	<b>14,282,104</b>	<b>13,759,573</b>	<b>522,531</b>	<b>28,041,677</b>	<b>65.3</b>
<b>ALL</b>		<b>22,055,033</b>	<b>20,892,839</b>	<b>1,162,194</b>	<b>42,947,872</b>	<b>100.0</b>

**Table IV****Summary Statistics**

Table lists the summary statistics for our variables. *VPIN* is the order flow toxicity metric calculated as in Equation (2). *Calls NBP (Puts NBP)* is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades. *Calls Imp. Volatility (Puts Imp. Volatility)* is the average of implied volatilities for calls (puts). *Calls Spread (Puts Spread)* is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote for calls (puts). *Slope* is one of the two measures of slope defined in Equation (1). *Index* is index level. *Index Return* is the index return computed from volume bar n-13 to n-1. *Real. Volatility* is realized volatility which is the sum of squared five-min returns during each day. *VIX* is the CBOE's volatility index for the S&P 500 index return.

<b>Variable Name</b>	<b>Min</b>	<b>Median</b>	<b>Max</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Skewness</b>	<b>Kurtosis</b>
VPIN	0.04	0.34	1.00	0.38	0.19	0.80	3.21
Calls NBP	-5678.46	15.17	16311.92	81.25	1201.35	2.01	26.36
Calls Imp. Volatility	0.07	0.10	0.18	0.10	0.02	0.93	3.51
Calls Spread	0.03	0.15	1.43	0.17	0.09	3.97	34.09
Puts NBP	-32395.32	45.15	6989.40	45.71	1224.09	-9.22	230.07
Puts Imp. Volatility	0.09	0.13	0.27	0.14	0.03	1.06	3.69
Puts Spread	0.04	0.13	0.68	0.14	0.06	3.02	16.45
ATM Calls NBP	-4128.43	0.54	9320.21	26.62	685.71	0.99	19.47
ATM Calls Spread	0.01	0.07	0.32	0.07	0.02	1.69	12.86
ATM Puts NBP	-32396.52	1.22	4725.65	16.15	998.57	-17.22	517.47
ATM Puts Spread	0.01	0.07	0.22	0.07	0.02	0.92	6.92
OTM Puts NBP	-3088.33	2.46	3232.77	35.80	478.48	0.16	9.20
OTM Puts Spread	0.02	0.10	0.31	0.11	0.03	1.09	7.10
DOTM Puts NBP	-2164.55	0.00	2373.45	-5.13	253.32	-0.42	14.36
DOTM Puts Spread	0.03	0.22	1.06	0.23	0.09	2.08	10.96
Slope <sub>1</sub>	-0.07	0.00	0.04	0.00	0.01	-2.11	26.78
Slope <sub>2</sub>	-0.05	0.02	0.09	0.02	0.01	0.87	5.43
Index	1219.73	1295.20	1431.59	1308.75	52.32	0.82	2.56
Index Return	-0.02	0.00	0.03	0.00	0.01	0.09	4.71
Real. Volatility	0.00	0.08	0.43	0.09	0.05	2.75	13.41
VIX	9.44	12.07	22.99	13.09	2.58	1.10	3.63

**Table V****Determinants of Slope of S&P 500 Index Options Skew**

Table presents the regression results of  $\Delta Slope_n = \alpha + \beta_1 \Delta Slope_{n-1} + \beta_2 R_n + \beta_3 Time_n + \beta_4 Spread_n + \beta_5 RV_n + \beta_6 NBP_n + \beta_7 VPIN_n + e_n$  where  $\Delta Slope_n$  is change in one of the two measures of slope defined in Equation (1) from volume bar  $n-1$  to  $n$ .  $R_n$  is the index return computed from volume bar  $n-13$  to  $n-1$  for the momentum effect.  $Spread_n$  is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and  $RV_n$  is realized volatility which is the sum of squared five-min returns during each day.  $Time_n$  is option's annualized time to maturity.  $NBP_n$  is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta for each moneyness category.  $VPIN_n$  is the metric for probability of informed trading and calculated as in Equation (2). \*\*\*, \*\*, \* denote statistical significance at the 1%, 5% and 10% levels respectively.

	$\Delta Slope_1$		$\Delta Slope_2$		
	Coefficient	t-value	Coefficient	t-value	
Intercept	-0.003	-3.334 ***	-0.006	-5.751 ***	
$\Delta slope_{n-1}$	-0.346	-20.466 ***	-0.379	-22.569 ***	
R	0.025	1.465	0.002	0.091	
Time	0.005	0.915	0.016	2.513 **	
Atm Call Spread	0.004	0.888	-0.007	-1.118	
Atm Put Spread	0.016	2.860 ***			
Otm Put Spread			0.040	8.927 ***	
RV	0.004	1.900 *	0.002	0.617	
Atm Call NBP	-0.014	-7.476 ***	-0.010	-4.442 ***	
Atm Put NBP	0.015	7.787 ***			
Otm Put NBP			0.014	4.205 ***	
VPIN	0.001	2.575 ***	0.002	2.438 **	

**Table VI**  
**Macroeconomic Announcements**

Table lists the macroeconomic announcements used in this study along with the category, timing in EST, source, frequency. Abbreviations are Investors Business Daily (IBD), Automatic Data Processing (ADP), Federal Reserve Board (FRB), Bureau of Labor and Statistics (BLS), Bureau of Economic Analysis (BEA), Bureau of the Census (BC), Conference Board (CB), US. Department of Labor (UDL), Institute for Supply Management (ISM), Federal Reserve Bank of Philadelphia (FRBP) and National Association of Realtors (NAR).

<b>Macroeconomic Announcement</b>	<b>Time</b>	<b>Source</b>	<b>Frequency</b>
ADP Employment Change	8:15	ADP	Five times
Unemployment Rate	8:30	BLS	Monthly
Initial Jobless Claims	8:30	UDL	Weekly
Consumer Price Index	8:30	BLS	Monthly
Unit Labor Costs	8:30	BLS	Eight times
GDP Price Index	8:30	BEA	Monthly
Producer Price Index	8:30	BLS	Monthly
Chicago Purchasing Manager	10:00	ISM	Monthly
Consumer Confidence	10:00	CB	Monthly
IBD/TIPP Economic Optimism	10:00	IBD	Six times
Philadelphia Fed.	12:00	FRBP	Monthly
Index of Leading Indicators	10:00	CB	Monthly
Housing Starts	8:30	BC	Monthly
Durable Goods Orders*	8:30	BC	Monthly
Factory Orders	10:00	BC	Monthly
Construction Spending	10:00	BC	Monthly
Business Inventories	10:00	BC	Monthly
Wholesale Inventories	10:00	BC	Monthly
Personal Income/Spending	8:30	BEA	Monthly
Retail Sales Less Autos	8:30	BC	Monthly
Capacity Utilization/Industrial Production	9:15	FRB	Monthly
Existing Home Sales	8:30	NAR	Monthly
New Home Sales	10:00	BC	Monthly

\*When there is also a GDP announcement that day, the durable goods orders announcement is made at 10:00 AM

**Table VII**  
**VPIN and Slope at Macroeconomic Announcement Times**

Table presents the regression results of  $\Delta Slope_n = \alpha + \beta_1 \Delta Slope_{n-1} + \beta_2 R_n + \beta_3 Time_n + \beta_4 Spread_n + \beta_5 RV_n + \beta_6 NBP_n + \beta_7 VPIN_n + \beta_8 News_n + \beta_9 (News_{k,t} * VPIN)_n + e_n$  where  $\Delta Slope_n$  is change in one of the two measures of slope defined in Equation (1) from volume bar  $n-1$  to  $n$ .  $R_n$  is the index return computed from volume bar  $n-13$  to  $n-1$  for the momentum effect.  $Spread_n$  is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and  $RV_n$  is realized volatility which is the sum of squared five-min returns during each day.  $Time_n$  is option's annualized time to maturity.  $NBP_n$  is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta for each moneyness category.  $VPIN_n$  is the metric for probability of informed trading and calculated as in Equation (2).  $News_n$  is a dummy variable that takes one for the volume bucket  $n$  that includes a macroeconomic announcement and zero otherwise \*\*\*, \*\*, \* denote statistical significance at the 1%, 5% and 10% levels respectively.

	$\Delta Slope_1$		$\Delta Slope_2$		
	Coefficient	t-value	Coefficient	t-value	
Intercept	-0.003	-3.223 ***	-0.006	-5.515 ***	
$\Delta Slope_{n-1}$	-0.345	-20.414 ***	-0.379	-22.597 ***	
R	0.025	1.485	0.004	0.167	
Time	0.005	0.908	0.016	2.510 **	
Atm Call					
Spread	0.005	0.897	-0.007	-1.113	
Atm Put Spread	0.016	2.872 ***			
Otm Put Spread			0.040	9.053 ***	
RV	0.004	1.897 *	0.001	0.588	
Atm Call NBP	-0.014	-7.476 ***	-0.010	-4.444 ***	
Atm Put NBP	0.015	7.789 ***			
Otm Put NBP			0.014	4.273 ***	
VPIN	0.001	2.290 **	0.001	1.745 *	
News	-0.001	-0.677	-0.003	-2.268 **	
News*VPIN	0.000	0.138	0.004	1.145	

**Table VIII**  
**VPIN and Slope with Macroeconomic Announcement Surprises**

Table presents the regression results of  $\Delta Slope_n = \alpha + \beta_1 \Delta Slope_{n-1} + \beta_2 R_n + \beta_3 Time_n + \beta_4 Spread_n + \beta_5 RV_n + \beta_6 NBP_n + \beta_7 VPIN_n + \beta_8 Surprise_n + \beta_9 (Surprise_{k,t} * VPIN)_n + e_n$  where  $\Delta Slope_n$  is change in change in one of the two measures of slope defined in Equation (1) from volume bar  $n-1$  to  $n$ .  $R_n$  is the index return computed from volume bar  $n-13$  to  $n-1$  for the momentum effect.  $Spread_n$  is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and  $RV_n$  is realized volatility which is the sum of squared five-min returns during each day.  $Time_n$  is option's annualized time to maturity.  $NBP_n$  is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta standardized by volume for each moneyness category.  $VPIN_n$  is the metric for probability of informed trading and calculated as in Equation (2).  $Surprise_{k,t}$  is defined as in Equation (4). \*\*\*, \*\*, \* denote statistical significance at the 1%, 5% and 10% levels respectively.

	$\Delta Slope_1$		$\Delta Slope_2$	
	Coefficient	t-value	Coefficient	t-value
Intercept	-0.003	-3.190 ***	-0.006	-5.573 ***
$\Delta slope_{n-1}$	-0.345	-20.348 ***	-0.379	-22.487 ***
R	0.028	1.630	0.004	0.175
Time	0.005	0.914	0.017	2.538 **
Atm Call				
Spread	0.005	0.942	-0.007	-1.057
Atm Put				
Spread	0.016	2.902 ***		
Otm Put Spread			0.040	9.067 ***
RV	0.003	1.777 *	0.001	0.455
Atm Call NBP	-0.014	-7.355 ***	-0.011	-4.566 ***
Atm Put NBP	0.015	7.800 ***		
Otm Put NBP			0.014	4.146 ***
VPIN	0.001	2.201 **	0.001	1.855 *
Surprise	-0.001	-1.562	-0.002	-2.467 **
Surprise*VPIN	0.001	0.687	0.003	1.297

**Table IX****Risk Neutral Skewness**

Table presents the regression results of  $\Delta Skew_n = \alpha + \beta_1 Kurt_n + \beta_2 R_n + \beta_3 Time_n + \beta_4 Spread_n + \beta_5 RV_n + \beta_6 NBP_n + \beta_7 VPIN_n + e_n$  where  $\Delta Skew_n$  is change in skewness from volume bar  $n-1$  to  $n$  and  $Kurt_n$  is defined in Equation (5).  $R_n$  is the index return computed from volume bar  $n-13$  to  $n-1$  for the momentum effect.  $Spread_n$  is the relative bid-ask spread, namely bid-ask spread divided by an option's mid quote and  $RV_n$  is realized volatility which is the sum of squared five-min returns during each day.  $Time_n$  is option's annualized time to maturity.  $NBP_n$  is the net buying pressure calculated as the difference between buyer motivated and seller motivated trades times the absolute value of delta for each moneyness category.  $VPIN_n$  is the metric for probability of informed trading and calculated as in Equation (2). \*\*\*, \*\*, \* denote statistical significance at the 1%, 5% and 10% levels respectively.

<b><math>\Delta Skew</math></b>			
	<b>Coefficient</b>	<b>t-value</b>	
Intercept	0.331	14.277	***
Kurtosis	-0.087	-22.459	***
R	-0.041	-0.108	
Time	-0.604	-5.076	***
Atm Call Spread	0.129	1.166	
Otm Put Spread	-0.116	-1.463	
RV	-0.084	-1.955	*
VPIN	0.043	3.474	***
Atm Call NBP	0.027	0.646	
Atm Put NBP	-0.067	-1.137	