Center of Volume Mass: Does Options Trading Predict Stock Returns?*

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Abstract We examine whether the distribution of trades along the set of strike prices of option contracts on the same stock contains information about underlying price discovery. We show that option traders' demand for *delta* exposure drives the volume-weighted average strike-spot price ratio ($VWKS$). In turn, we find that $VWKS$ predicts underlying returns and anticipates the flow of fundamental information about the stock. The return predictability is greater but not limited to stocks with higher information asymmetries and arbitrage costs, and becomes stronger ahead of value relevant news. Overall, options trading appears to play an important informational role for underlying markets.

Keywords: Options; Volume; Return predictability; Information; Center of mass

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1 Introduction

Whether activity in equity derivatives plays a role in the price discovery process of the underlying stocks is a long standing question (e.g., see Biais and Hillion (1994) and Easley, O'Hara, and Srinivas (1998)). Recent empirical studies in this line of research show that aggregate trading volume across option contracts on the same stock explains the underlying price dynamics (e.g., Roll, Schwartz, and Subrahmanyam (2010), Johnson and So (2012), and Ge, Lin, and Pearson (2016)). While they are suggestive of feedback effects between options and equity markets, these findings raise at least two important questions. First, given the typically large number of different option contracts on a stock, it seems natural to inquire whether the distribution of trading volume among available contracts contains incremental information about underlying price dynamics. Prior studies such as Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006) mostly focus on the distinction between call and put options volumes, while another important feature of those contracts, the moneyness, is only analyzed at a coarse granularity by distinguishing between in-the-money (ITM), at-the-money (ATM), and out-of-the-money (OTM) contracts. In this study, we examine whether the shape of the volume distribution along available option contracts with different moneyness contains information about future stock price dynamics. To the best of our knowledge, such analysis is novel to the financial literature.

Second, a question remains as to the mechanism that drives the stock return predictability associated with options trading volumes. Prior studies typically infer informed trading in options from the evidence of return predictability. There are, however, other reasons why option volumes might predict underlying returns - for example, due to price pressure from options market makers' delta hedging activities. In our tests, we examine whether the flow of information about the stock drives the dynamics of its option volume distribution and the associated return predictability. In this context, in addition to examining a comprehensive set of value relevant news events, we exploit transitory price jumps unrelated to firm fundamentals to design a falsification test that sheds light on the underlying mechanism.

We rely on the volume-weighted strike-spot ratio to characterize the central location of the distribution of trading activity along the moneyness of available option contracts on the same stock. The ratio of the contract's strike price (K) and the underlying stock price (S) measures the option moneyness, whereby call (put) options are out-of-the-money when K/S is above (below) one. After normalizing K/S by subtracting one, we calculate the weighted average of the normalized K/S ratio across available contracts using as weights the number of lots traded on each contract during the same period ($VWKS$, hereafter). $VWKS$ reflects the center of mass in the options volume distribution along strike prices of available contracts and takes on higher (lower) values when the trading volume is tilted more toward OTM (ITM) calls and ITM (OTM) puts. Admittedly, there are other ways to describe the option volume distributions, most being more complex. Our intuitive nonparametric approach provides a flexible statistic that reflects key aspects of the heterogeneity in the level of activity among diverse options written on the same stock.

Our empirical approach is motivated by some stylized facts about options trading that suggest $VWKS$ reflects option traders' demand for directional exposure to the underlying stocks. A recent study by Hu (2014) shows that options traders are net buyers of OTM options and net sellers of ITM options for both calls and puts.[1] As such, trades of puts and calls at the same strike price would typically reflect the demand for similar risk exposure to underlying price movements. In particular, option traders' net demand for calls (puts) is more likely positive (negative) in the high K/S region, where calls (puts) are OTM (ITM), when they seek positive *delta* exposure, and the opposite holds when they seek negative exposure. While $VWKS$ uses unsigned volumes without distinction between call and put option trades occurring at the same strike price, prior evidence implies that it should reflect

[1] Hu's (2014) results are based on signed options tick data from the Options Price Reporting Authority across all options exchanges in the US between 2008 and 2010. The net demand is more balanced in the Chicago Board Options Exchange (CBOE) between 1990 and 2001 as reported by Pan and Poteshman (2006) using daily aftermarket data. However, Pan and Poteshman find the same pattern of net demand as in Hu (2014) for position-opening transactions, which are more informative about future returns. Between 1996 and 2001, Garleanu, Petersen, and Poteshman (2009) report negative net demand for all types of options on single-name stocks using the same data from CBOE though.

options traders' demand for directional exposure to underlying price movements (i.e., *delta* exposure). It is worth noting that a similar logic does not apply to option traders' demand for exposure to underlying volatility (*vega*) or jump (*gamma*) risks because buying calls and selling puts at the same strike price lead to opposite exposure on those dimensions. Therefore, $VWKS$ should only identify option traders' net demand for *delta*.

We verify the validity of this premise empirically by examining the relation between $VWKS$ and options traders' demand for different options based on open/close position data from the International Securities Exchange (ISE) between 2006 and 2014. The results of our analysis show that option traders' net buying of *delta* is a statistically significant and robust determinant of $VWKS$ in the cross-section. Conversely, we find no evidence that option traders' net demand for *vega* or *gamma* exposure explains cross-sectional variation in $VWKS$. Therefore, consistent with the premise of our empirical approach, variation in options traders' demand for directional exposure to underlying price movements indeed determines the cental location of the option volume distribution along contract moneyness in the cross-section of stocks.

Given its link to option traders' net demand for *delta* exposure, $VWKS$ may relate to future underlying price discovery in several ways. First, there can be a positive and permanent association, if some traders use options to profit from private information (e.g., Black (1975), and Easley, O'Hara, and Srinivas (1998)). Second, order imbalances in the options market lead to delta hedging trades by options market makers. When options traders seek long (short) *delta* exposure without hedging, market makers will be short (long) in *delta*. Consequently, market makers may establish long (short) positions in the underlying market to hedge their open option positions. Even if the primitive trades in options are not informed, market makers' hedging trades may generate price pressure in the underlying market. However, unlike the information channel, this price pressure channel should result only in temporary price adjustments that subsequently revert to the unchanged fundamental value. Lastly, the demand for *delta* exposure in the options market may covary with the demand in the underlying market, which may or may not be driven by fundamental information. Given that there is a negative relation between $VWKS$ and contemporaneous stock order imbalances and returns in the ISE data, $VWKS$ may also have predictive ability due to subsequent return reversals. Although all three channels imply a positive relation between $VWKS$ and immediately subsequent underlying returns, only the information channel predicts a permanent price impact that anticipates the arrival of fundamental information.

To conduct our tests, we compute the daily $VWKS$ for each optionable stock from 1996 to 2016. We then begin our main analysis by examining the underlying returns associated with univariate portfolio sorts based on $VWKS$. We find that a value-weighted investment portfolio long in high $VWKS$ stocks (i.e., top decile) and short in low $VWKS$ stocks (i.e., bottom decile) earns a statistically significant average abnormal return of more than 13.4 basis points (bp) on the following day, or approximately 40% per year. The return of the same long-short portfolio formed on day t is also positive and significant, albeit smaller in magnitude, during the next four trading days ($t + 2$ to $t + 5$) before it becomes statistically insignificant. Moreover, we find no evidence of reversal, as abnormal returns are not significantly different from zero on any of the remaining trading days in the 21-day window we examine. This permanent price impact associated with $VWKS$ rules out the notion that the association between $VWKS$ and subsequent underlying returns stems from temporary price pressure due to options market makers' delta hedging trades.

An immediate concern is that our results may reflect $VWKS$'s correlation with other options or equity market predictors for stock returns. To evaluate this concern, we conduct a double sorting analysis. Specifically, first, we independently sort stocks each day into quintiles by lagged stock returns, option-to-stock volume ratio (OS), and seven other well-known return predictors from the options market. Then, we reexamine the profitability of the $VWKS$ strategy within each of these 45 portfolios. We find that the average abnormal returns and Fama and French (2015) five-factor alphas from the $VWKS$ strategy are positive and significant in 43 out of 45 portfolios. The double sorting analysis using past stock returns and OS also sheds additional light on the predictability of underlying returns associated with $VWKS$. The returns to the $VWKS$ strategy are positive and significant in all quintiles sorted on past returns, which suggests that its profitability is not due to stock return reversals. Moreover, the profitability of the $VWKS$ strategy increases monotonically from low to high OS quintiles, which suggests that the the link between $VWKS$ and subsequent underlying returns becomes stronger when options traders are more active. These results indicate that the source of the return predictability is indeed rooted in the options market activity rather than liquidity-driven price reversals in the underlying market, in contrast with Goncalves-Pinto et al.'s (2019) findings.

To probe the robustness of our portfolio sorting results, we estimate the relation between $VWKS$ and subsequent underlying returns in a multiple regression setting, while controlling for known return predictors from both options and equity markets. Our Fama-MacBeth (1973) estimates indicate that higher $VWKS$ predicts higher subsequent returns in the underlying stock up to a week, and this relation is statistically significant at a 1% probability level. In additional robustness tests, we obtain similar results when we predict raw returns instead of risk-adjusted returns, use a log-transformation of K/S or option *delta* instead of K/S in measuring the center of volume mass, or compute $VWKS$ using lagged stock prices to further address concerns about short-term return reversals. Overall, we continue to find a strong and robust relation between the distribution of volume across available options contracts and subsequent underlying returns.

If the link between $VWKS$ and stock returns stems from options traders anticipating the arrival of news about the underlying, the link should be stronger among stocks that are more opaque or harder to arbitrage - as larger mispricing of the underlying makes informed options trading more profitable. We test this prediction by repeating our baseline tests across subsamples based on various stock characteristics that are typically used as proxies for opaqueness or arbitrage costs. To that end, we sort stocks into terciles based on market capitalization, analyst coverage, institutional ownership, probability of informed trading (PIN), Amihud's (2002) illiquidity, bid-ask spread, and idiosyncratic volatility. When we compare stocks across extreme terciles, the results reveal two important facts. On the one hand, we find that the link between $VWKS$ and subsequent returns is positive and statistically significant in all of the aforementioned subsamples. Thus, different from most other return predictors, informed trading in options and the resulting predictive ability of $VWKS$ is not confined to stocks that are typically harder to trade. On the other hand, consistent with our prediction, the link between $VWKS$ and subsequent underlying returns is in fact stronger among stocks that are more opaque or harder to arbitrage (i.e. low market capitalization, low institutional ownership, high PIN, low liquidity, and high idiosyncratic volatility), particularly in the first half of our sample period.

Next, to test a direct implication of the information channel hypothesis, we examine whether the flow of news about a stock does in fact explain variation in $VWKS$. For these tests, we characterize as 'news event dates' those days associated with: the disclosure of earnings announcements and other material events via an 8-K filing; the occurrence of permanent vs transitory stock price jumps without a corresponding 8-K filing, following Savor (2012) and Boehmer and Wu (2013). We differentiate earnings announcements from other 8-K filing events because the timing (if not the content) of the former is typically anticipated, while the latter are generally not. This allows us to assess whether the patterns in $VWKS$ around the arrival of information depend on whether the timing of the event is widely anticipated. We distinguish permanent from transitory price jumps because only the former should reflect valuable signals about underlying fundamentals, which we argue drive informed options trading. In this sense, transitory jump events provide a valuable opportunity for a placebo test of our main conjecture that variation in $VWKS$ reflects options traders' private information about underlying fundamental value.

The evidence shows that the *pre-event* patterns in $VWKS$ vary widely across the different types of events that we examine. Specifically, we find that $VWKS$ has significant abnormal run-ups ahead of both scheduled and unscheduled 8-K filings in the same direction of the news. But the abnormal run-up starts earlier ahead of scheduled events than unscheduled events. Thus, consistent with our main conjecture, options trading tilts toward contracts with higher (lower) strike prices prior to the disclosure of positive (negative) news and more so when the event is widely anticipated. Moreover, consistent with the idea that options traders acting on upcoming fundamental news drive $VWKS$, we find that the abnormal run-up occurs only when the resulting price adjustment is permanent. In sharp contrast, there is no evidence that options volume tilts in the direction of future price jumps that quickly revert and are unlikely to be driven by fundamental information.

To conclude our analysis, we examine whether the signal embedded in $VWKS$ about subsequent stock returns varies with the underlying flow of information. In principle, we expect a stronger link between $VWKS$ and subsequent underlying returns when informed options trading is likely to play a greater role in determining $VWKS$. In line with this prediction, the evidence shows that the informativeness of $VWKS$ with respect to future stock returns is higher ahead of corporate news events that are unscheduled or associated with permanent price jumps. These incremental effects are statistically significant and economically large (more than 2.5 times the unconditional price sensitivity to $VWKS$). Overall, supporting our inference that $VWKS$ reflects the activity of options traders informed about underlying fundamentals, we find that $VWKS$ and its ability to predict underlying returns depend on the future flow of information about the stock.

Our analysis makes an important contribution to the literature on lead-lag relations between the outcomes of separate financial markets. We are the first to show that the distribution of options volume across strike prices contains valuable information about the underlying, which is neither reflected in current spot prices nor subsumed by other well known return predictors. Moreover, our results have methodological implications for future research and applications in this area of inquiry. While prior studies find that aggregate unsigned options volume predicts future stock returns due to short selling in the underlying (e.g., Johnson and So (2012)), our results imply that the location of the unsigned options volume along the set of strike prices contains directional stock price information that need not be related to short selling in the underlying. Therefore, our proposed measure is apt to extracting underlying price information from options trading activity *without* relying on proprietary options tick or position data, which tend not to be widely available. In a related study, Kang, Kim, and Lee (2018) examine return predictability of the ratio of OTM calls volume to OTM puts volume. This measure exploits part of the options volume distribution and is closely related to the put-call ratio of Pan and Poteshman (2006). In contrast, our empirical approach extracts information from the *full* distribution of options trading volume to identify its central location across all available contracts.

Last but not least, our evidence establishes a direct link between the predictive ability of options trading volume vis-à-vis underlying returns and fundamental information. We find that the return predictability of $VWKS$ is persistent and orthogonal to past returns of underlying stocks, and strengthens when the options market is active. These results are not consistent with liquidity-based explanations of our main findings. Two recent studies examine the options trading strategies of informed investors ahead of value relevant corporate events and report evidence that is consistent with our results on the relation between underlying information flow and aggregate activity in options market (i.e., Augustin, Brenner, Grass, and Subrahmanyam (2018), Cremers, Fodor, Muravyev, and Weinbaum (2019)). However, while other studies examine option activity around specific news events such as earnings announcements, our analysis is based on a large, comprehensive, and diverse set of events (i.e., 8-K filings and price jump events). This allows a more granular analysis of whether the arrival of (future) information drives current option market activity and the associated return predictability. In this context, transitory price jumps provide a unique opportunity to conduct a placebo test new to this literature.

2 Related literature and hypotheses

Investors endowed with private information have incentives to trade options given the high leverage embedded (Black, 1975) and the lack of short selling constraints (Figlewski and Webb, 1993). Theories such as Biais and Hillion (1994) and Easley, O'Hara, and Srinivas (1998) show that when the options market is liquid enough, it is optimal for informed agents to trade both stocks and options. As a result, options trading volumes will reflect private information about future underlying prices. Several empirical studies report evidence supporting this claim using options order flow (e.g., Easley, O'Hara, and Srinivas (1998), Pan and Poteshman (2006), and Hu (2014)). Unlike prior studies using intraday data to compute options order flow, Roll, Schwartz and Subrahmanyam (2009) propose using total options volume as a proxy for informed trading activity and show that theoretically the level of option market activity should predict future firm value. Using the total options-to-stock volume ratio (O/S, henceforth) to test this idea, Roll, Schwartz and Subrahmanyam (2010), Johnson and So (2012), and Ge, Lin, and Pearson (2016) find evidence consistent with O/S reflecting information about future underlying prices.

The O/S measure, however, does not differentiate between trades executed on fundamentally distinct option contracts (e.g., put vs. call, maturity, strike price). If the choice of contracts traded itself contains information about future underlying prices, as it is conceivably the case, the O/S measure will not reflect this link by design. Among the features that may lead a trader to select one contract over another, the strike price is arguably one of the most important, as it determines the contract's intrinsic value and *moneyness*. Trading in-the-money (ITM) options and out-of-the-money (OTM) options can result in very different risk exposures to underlying price movements. Thus, the trading volumes in contracts that have different strike prices should reflect different incentives and objectives of the corresponding traders. Our main conjecture is that trading by investors endowed with private information about the underlying has a meaningful systematic impact on the distribution of options trading volumes along the set of available strike prices. Correspondingly, we expect that the distribution of options volumes along strike prices contains valuable information about future underlying price movements.

In the US equity options market, the strike price (K) interval is 2.50 points for stocks under \$25, 5 points for stocks over \$25 per share, and 10 points (or greater) is acceptable for stocks over \$200 per share. In and of itself, K contains no meaningful information about the underlying. However, given the underlying spot price (S), the volume distribution across option contracts with different K's will contain valuable information, if informed traders optimize their choice of contracts. Informed traders have incentives to buy OTM options because they provide higher leverage. However, they would avoid deep OTM contracts because those options are usually less liquid and may expire out of the money even after the private information is priced in. As the magnitude of the private signal increases, the investor has stronger incentives to trade contracts that are further in the OTM region. As the precision of the signal increases, the investor has stronger incentives to trade larger volumes at the optimal strike. Although the first two moments of the private information signal affect different aspects of informed traders' decisions, the end result is the same with respect to the center of options volume mass. In particular, as private information becomes more valuable (i.e., larger magnitude or greater precision of the private signal), the options volume distribution becomes more skewed toward strike prices that are closer to the privately known fundamental value of the underlying. In other words, informed traders' activity pushes the center of volume mass toward the optimal strike price in the direction of the signal. This effect is further amplified when informed traders also sell ITM options to profit on private information.

In light of these considerations, we propose that the volume-weighted average strike price of traded option contracts contains valuable information about future underlying price movements. To allow comparisons across different underlying stocks, we normalize (i.e., divide) the strike prices of contracts by the underlying spot price (S) and subtract one from this ratio. We refer to the normalized volume-weighted strike-spot price ratio as

$VWKS$. If there is informed trading in options, we expect that it would contribute to the price discovery process of the underlying and $VWKS$ should predict subsequent underlying stock returns. Formally, this logic leads to the following testable hypothesis.

Hypothesis 1. *Higher volume-weighted strike-spot price ratios, $VWKS$, precede (and thus predict) higher and permanent changes in the underlying stock prices.*

To the extent that $VWKS$ reflects options traders' demand for directional exposure to underlying price changes unrelated to fundamental information, it may predict underlying returns via a liquidity channel. Specifically, as options market makers engage in *delta* hedging as a standard practice, option traders' demand for *delta* exposure may translate into price pressure in the underlying market. This non-information channel could also generate a positive price impact on the underlying stock. However, such impact should be short-lived. As the price pressure eases, the stock price would revert to its fundamental value, resulting in short-term return reversals. Hence, to disentangle the two channels leading to return predictability, we test whether variation in $VWKS$ gives rise to systematic return reversal patterns.

To ensure that any return predictability associated with $VWKS$ is not spurious, we conduct double sort portfolio tests and multiple regression analyses that isolate the incremental effect of $VWKS$ on the underlying price discovery related to other known predictors of stock returns. In addition to the O/S ratio, Pan and Poteshman (2006) find that the ratio of put-to-call trading volumes (PC) is negatively associated with future stock returns. Several studies find that options implied volatilities are systematically correlated with future returns. For example, Cremers and Weinbaum (2010) find that larger deviations from put-call parity (DEV) predict higher returns at the weekly horizon and they interpret their results as evidence of mispricing in the stock market. Xing, Zhang, and Zhao (2010) find that higher options-implied skewness ($SKEW$) predicts higher underlying stock returns up to six months. Guo and Qiu (2014) confirm the idiosyncratic volatility puzzle using options-implied volatility ($IVOL$). An, Ang, Bali, and Cakici (2014) find that larger innovations in implied volatilities from both call ($DCIVOL$) or put ($DPIVOL$) options predict higher underlying stock returns. Baltussen, Van Bekkum, and Van Der Grient (2018) find that stocks with low variance of implied volatility ($VOLVOL$) outperform stocks with high $VOLVOL$. In our tests, we control for all of these options market-based predictors as well as for past returns, bid-ask spreads, and turnover ratios of the underlying stock, which are also known to predict returns and may be correlated with $VWKS$.[2]

Incentives to collect and trade on private information increase with the likely mispricing of the underlying stock. Namely, the magnitude of the potential profits available to informed options traders increases when the underlying stock's information environment is more opaque or its mispricing is harder to arbitrage. Therefore, if our main conjecture is borne out in the data, we expect that informed investors trade options more intensely and thus amplify the predicted baseline effects when the underlying stock is traded in a more opaque information environment or it is harder to arbitrage. The following hypothesis summarizes the testable implications of this line of reasoning.

Hypothesis 2. *The relation between volume-weighted strike-spot price ratio, $VWKS$, and subsequent underlying returns is stronger for stocks associated with more severe information asymmetry or higher arbitrage costs.*

To test this hypothesis, we rely on several proxies for information asymmetry commonly

[2]Goncalves-Pinto et al. (2019) attribute return predictability associated with options market characteristics to short-term stock return reversals. Because options trading volumes are usually much lower than in the underlying markets, they argue that options market makers do not update option prices quickly enough when the underlying price moves due to liquidity reasons. When underlying prices later reverts to fundamental value, the inertial options prices may not respond to the preceding price pressure in the underlying markets, resulting in a spurious correlation. Our controls for past stock returns, bid-ask spreads, and turnover ratios as well as for options market-based predictors should subsume such effects. Moreover, if $VWKS$'s predictive ability arises from informed traders' active use of options, the predictability should strengthen when options trading is more active. Alternatively, if $VWKS$'s predictive ability results from price updating of illiquid options being slower than underlying price reversals, the predictability should be stronger when the options market is less active. Given this contrast in the predictions, our a double-sorting analysis on O/S and $VWKS$ can distinguish the relative importance of two mechanisms.

used in the literature, including firm size, analyst coverage, institutional ownership, and the probability of informed trading (PIN) as in Easley, Kiefer, O'Hara, and Paperman (1996). To proxy for arbitrage costs, we rely on similarly widely used measures including Amihud's (2002) illiquidity, relative bid-ask spreads, and idiosyncratic volatility.

To establish a more direct link between information flow and options trading, existing studies tend to focus on specific information events.[3] In our analysis, we cast a wide net when identifying news event days. To begin, we classify as event days those corresponding to the mandated disclosure of material corporate information via 8-K filings.[4] We further distinguish between events that are *scheduled*, for filings reporting earnings announcements, versus *unscheduled*, otherwise.[5]

Alternatively, after excluding 8-K filing dates, we classify as news event days those associated with large jumps in the underlying price, i.e., exceeding 10% in absolute value or two standard deviations of the daily returns in the past 21 trading days. We further segment these event days depending on the nature of the corresponding price jump. Specifically, following Boehmer and Wu (2013), we separate *transitory* jumps, i.e., reverting within 5 trading days, from those that are more *permanent* in nature and, thus, more likely to reflect the arrival of news about the stock's fundamental value. A notable benefit of using this finer classification is that transitory price jumps are unlikely to reflect meaningful fundamental news and as such provide a valuable opportunity to conduct placebo tests of our hypotheses pertaining to the flow of information.

[3] For example, various studies examine the equity pricing effects associated with options volumes around earnings announcements (e.g., Pan and Poteshman (2006), Roll, Schwartz and Subrahmanyam (2010), Xing, Zhang, and Zhao (2010), Johnson and So (2012), and Ge, Lin, and Pearson (2016)). However, the anticipated nature of earnings announcements may affect expected volatility and thus contaminate the relation between underlying returns and options trading as shown by Cremers, Fodor, Muravyev, and Weinbaum (2019). Examining unscheduled news events bypasses this issue at least in part (e.g., Cao, Chen, and Griffin (2005), Chan, Ge, and Lin (2015), and Augustin, Brenner, and Subrahmanyam (2018) for mergers and acquisitions, Hayunga and Lung (2014) for analyst revisions, Augustin, Brenner, Hu, and Subrahmanyam (2018) for spinoffs, Gharghori, Maberly, and Nguyen (2015) for stock splits, and Ge, Hu, Humphery-Jenner and Lin (2016) for bankruptcies).

[4] See Section 13 and 15(d) of The Securities Exchange Act of 1934.

[5] The vast majority of 8-K's are unrelated to earnings announcements and thus the corresponding events are largely unscheduled based on our classification.

Overall, the basic tenet of our conjecture (i.e., informed trading in options drives the location of the volume distribution along strike prices) implies that $VWKS$ should predict the flow of future news about the underlying in the direction of the information signal. Correspondingly, we expect that the link between subsequent stock returns and $VWKS$ becomes stronger ahead of the arrival of fundamental information about the firm, especially when the news has a large permanent price impact or is not widely anticipated. The following two hypotheses formalize the testable implications of this logic.

Hypothesis 3. *The volume-weighted strike-spot price ratio, $VWKS$, varies ahead of the arrival of fundamental information about the underlying equity (i.e., scheduled or unscheduled 8-K's or permanent price jumps) in the direction of the information signal.*

Hypothesis 4. *The strength of the relation between the volume-weighted strike-spot price ratio, $VWKS$, and subsequent underlying returns increases ahead of the arrival of fundamental information about the underlying equity (i.e., scheduled or unscheduled 8-K's or permanent price jumps).*

3 Data

3.1 Sample selection and variable construction

We obtain options data from OptionMetrics, including daily options trading volumes, strike prices, expiration dates, option *delta*, as well as call and put indicators starting from 1996. Daily stock returns, bid-ask spreads, trading volumes, and number of shares outstanding are from the Center for Research in Security Prices (CRSP). We also require the stock to have information in Compustat and New York Stock Exchange's Trade and Quote (TAQ) databases so that we can compute its book-to-market ratio and stock order flow. Our main sample ends in 2016. We focus on common stocks only (CRSP share codes 10 and 11) and exclude all indexes, units, ADRs, REITs, closed end funds, ETFs, and foreign firms. As standard in this literature (e.g., Jegadeesh and Titman (2001)), we exclude stocks whose closing price is below \$5. After merging data from these various sources, our final sample comprises 3,837 unique stocks from 1996 to 2016, with an average of 1,200 unique stocks per day.

We use the volume-weighted strike-spot ratio for stock i on day t, $VWKS_{i,t}$, to measure the center of mass in the options volume distribution along strike prices of option contracts linked to the same underlying stock:

$$VWKS_{i,t} = \frac{\sum_{j=1}^{n} volume_{i,t,j}(\frac{K_{i,t,j}}{S_{i,t}} - 1)}{\sum_{j=1}^{n} volume_{i,t,j}}, \tag{1}$$

where $K_{i,t,j}$ is the strike price for contract j, $volume_{i,t,j}$ is the trading volume of contract j, n is the total number of unique option contracts linked to stock i with maturity in more than 10 calendar days. We exclude near-expiration contracts because a large portion of trading activity in these contracts can be associated with rolling although we achieve qualitatively the same results using alternative maturity filters or without any maturity filter in unreported tests. $S_{i,t}$ is the underlying stock price. If no options on stock i are traded on day t, we set $VWKS_{i,t}$ to zero.[6]

Table 1 reports summary statistics for both options and equity market-based variables used in our main analysis. Both options and equity trading volumes are expressed in terms of number of shares traded. All variables are winsorized at the 0.5^{th} and 99.5^{th} percentiles every day to mitigate the effect of extreme outliers.

[Table 1 about here]

Our measure, $VWKS$, tends to be slightly above zero on a typical day, with a mean of 0.018 and a standard deviation of 0.105. Thus, the typical daily mass of options volume

[6]If we fill missing $VWKS$ with the last available non-missing values, we obtain very similar results.

along strike prices is skewed to the right, implying more OTM calls and ITM puts are traded than ITM calls and OTM puts. In our tests of the equity pricing effects of $VWKS$, we control for a host of other stock and options market-based factors that are known to predict stock returns. The Appendix contains detailed definitions for all control variables, while Table 1 shows that the summary statistics of those variables are in line with prior literature.

3.2 Determinants of $VWKS$

Our main conjecture about the relation between $VWKS$ and the underlying price discovery process rests on the premise that $VWKS$ reflects options traders' demand for *delta* exposure. Therefore, before proceeding with our main analysis, we directly test this premise by examining the determinants of $VWKS$. To conduct this analysis, we obtain data on all open and close option positions from the International Securities Exchange (ISE) between 2006 and 2014. These data reflect all positions opened and closed on each day by non-market makers for each available option contract.[7] Using contract-level positions, we define options traders' net order flow as the total buy volume minus the total sell volume by non-market makers. We then merge the contract order flow with the contract's Greeks in OptionMetrics using the common option contract ID. After multiplying each contract order flow by the corresponding option delta, we aggregate delta order flows across all contracts on the same stock to measure option traders' net demand for delta exposure ($NetBuyISE\_Delta$) on each day. We also compute their net demand for exposure to vega ($NetBuyISE\_Vega$) and gamma ($NetBuyISE\_Gamma$) in a similar fashion. Lastly, we calculate $VWKS$ using only ISE trading volumes, $VWKS\_ISE$. Because ISE is but one of many exchanges where options trade during our sample period, examining the impact of $NetBuyISE\_Delta$ on both $VWKS\_ISE$ and $VWKS$ speaks to whether the results can be generalized to the whole options market. On average, 656 stocks have options traded

[7] A detailed description of the data can be found in Ge, Lin and Pearson (2016).

on ISE per day, about half of all stocks with options in our main sample.

Using the ISE restricted sample, we estimate the following model following Fama-MacBeth's (1973) approach to test the implications of our premise that $VWKS$ varies directly with $NetBuyISE\_Delta$:

$$VWKS_{i,t} = \alpha + \beta NetBuyISE\_Delta_{i,t} + \theta X_{i,t} + \epsilon, \tag{2}$$

where $NetBuyISE\_Delta_{i,t}$ is the same-day measure of option traders' net purchase of delta exposure, $X_{i,t}$ is the set of control variables including $NetBuyISE\_Vega$ and $NetBuyISE\_Gamma$ as well as the order imbalance of the underlying stock based on Lee and Ready (1991) algorithm, the underlying stock return, and the volume-weighted options return (VW_OPTRET). Table 2 reports the model coefficient estimates and t-statistics based on Newey and West (1987) standard errors.

[Table 2 about here]

Columns (1) and (2) report simple and multiple regression results, respectively, when the dependent variable is $VWKS\_ISE$. In Column (1), the estimated coefficient on $NetBuyISE\_Delta$ is 0.058 with a t-statistic of 19.15, indicating a strong positive relation between options traders' demand for delta exposure and the center of volume mass measured using ISE data alone. When we include all other controls in Column (2), we find that the coefficient estimate for $NetBuyISE\_Delta$ retains the same order of magnitude and statistical significance. In contrast, neither $NetBuyISE\_Gamma$ nor $NetBuyISE\_Vega$ has a significant coefficient in the regression. For the other control variables, both stock returns and order flows take on negative and significant coefficients and the value-weighted options returns have a positive and significant coefficient. When we use $VWKS$ computed using trading volumes across all options exchanges in Columns (3) and (4), we find that all the results remain qualitatively the same. Overall, Table 2 shows that there is a robust positive relation between $VWKS$ and options traders' net demand for delta, but not vega or gamma. The robust negative relation between $VWKS$ and underlying stock returns, however, suggests that return reversals may result into a spurious positive correlation between $VWKS$ and subsequent underlying returns, an issue that we address explicitly in our asset pricing tests.

4 $VWKS$ and price discovery

4.1 Portfolio analysis

To gauge the relation between $VWKS$ and subsequent underlying returns, we begin by performing a univariate portfolio analysis. In particular, for each trading day, we form decile portfolios based on $VWKS$. The portfolios are value-weighted based on market capitalization to reduce the impact of small stocks on our results.[8] We then examine the performance of a strategy that buys stocks in the highest decile and sells those in the lowest decile on the next day. For comparison, we also repeat a similar analysis for the other options market-based predictors. Table 3 reports the mean daily mid quote returns of the long-short portfolios as well as their alphas adjusted for Fama-French (2015) and a momentum factors. The t-statistics reported in the table are based on Newey-West (1987) standard errors.

[Table 3 about here]

Table 3 shows that the long-short portfolio formed on $VWKS$ yields large mean daily raw or risk-adjusted returns, above 13.4 basis points (bp) before transaction costs (or 40% annualized), which are highly statistically significant. Although the annualized returns may seem high, transaction costs are likely to have a substantial drag on the documented performance. Zooming in on the strategy, it is worth noting that both the long and short

[8]We obtain stronger results when we use equal-weighted portfolios.

legs of the strategy contribute to the return differential, with a mean daily return for the high (low) decile portfolio of 9.38 bp (-4 bp). The estimated alpha of the $VWKS$ strategy is of similar magnitude and statistical significance. Moreover, in untabulated analysis, we find that the strategy based on $VWKS$ generates consistent profits during each calendar year in our sample period, including those corresponding with the financial crisis of 2007-2009. Most of the other options market-based strategies also generate statistically significant profits based on univariate portfolio sorts except the one based on volatility of volatility ($VOLVOL$). However, the abnormal returns from other strategies are typically smaller except for the strategy based on deviations from put-call parity (DEV) of Cremers and Weinbaum (2010), which generates an alpha of 13.9 bp comparable to the 13.8bp of the $VWKS$ strategy.

To investigate the long-term relation between $VWKS$ and underlying returns, we estimate daily alphas of the long-short portfolio formed on day t up to 21 trading days (i.e., a month) later. Figure 1 plots these estimated alphas as well as their 90% confidence intervals. As shown in the figure, $VWKS's$ immediate price impact on day $t+1$ is the largest. However, the daily alpha estimates remain positive and statistically significant up to day $t+5$. After five trading days from the portfolio formation, the alpha estimates remain predominantly positive but are never significantly different from zero. This evidence shows that there is no reversal in the predictability of underlying returns associated with $VWKS$ for up to a month after the portfolio formation. This test arguably sets a higher hurdle than simply skipping a day after portfolio formation to avoid potential impact from stock return reversal as suggested by Goncalves-Pinto et al. (2019). Moreover, we find similar results from tests based on weekly portfolio sorts as shown in Table A1 of the Online Appendix.

[Figure 1 about here]

Given that eight out of nine strategies relying on options market-based predictors other than $VWKS$ yield significant returns, it is natural to question whether the signal embedded in $VWKS$ has incremental value. Moreover, slow option price updating and stock return reversal remain a concern for our information-based explanation. To address these questions, we repeat the portfolio analysis of $VWKS$ following a double sorting approach. In particular, first, we sort stocks into quintile portfolios based on the rankings of past stock returns or one of the options market-based predictors other than $VWKS$. Then, within each of these quintile portfolios, we sort stocks into quintiles based on the $VWKS$' rankings. Finally, we form long-short investment portfolios using the high-minus-low quintile portfolios of $VWKS$. As before, all portfolios are value-weighted using each stock's market capitalization. Table 4 presents the results of this analysis, including the mean daily returns, alphas, and Newey-West (1987) t-statistics for the long-short portfolios based on $VWKS$.

[Table 4 about here]

Each panel in Table 4 reports results based on a distinct first-step sorting variable, namely: $QRET$ (Panel A), OS (Panel B), PC (Panel C), DEV (Panel D), $SKEW$ (Panel E), $IVOL$ (Panel F), $DCIVOL$ (Panel G), $DPIVOL$ (Panel H), or $VOLVOL$ (Panel I). Altogether, there are 45 long-short portfolios formed on the basis of $VWKS$ within the sorted quintiles of the other nine predictors. We find 44 of the 45 long-short strategies that we test yield positive daily raw or risk-adjusted returns. The estimated performance is statistically significant at least at the 5% probability level in 43 of the 45 portfolios. The results of the double sorting analysis confirm that $VWKS$ contains valuable information about subsequent underlying returns. Moreover, the results in the first two panels based on past returns ($QRET$) and option-to-stock volume ratio (OS) are particularly informative with respect to the channels that may give rise to the underlying return predictability associated with $VWKS$. If the predictive ability of $VWKS$ is a combined effect of slow option price updating and underlying return reversal, we would expect the predictability to concentrate on only the high and low $QRET$ portfolios (where return reversal effect is stronger), and to decrease in OS (when active trading makes options prices less stale). On the contrary, In Panel A, the $VWKS$ strategy generates positive and significant abnormal returns in all quintile portfolios based on $QRET$. Although the effect is stronger in the high $QRET$ quintile, the variation in the other four quintile portfolios is small. Panel B shows that the profitability of the $VWKS$ strategy becomes larger when OS increases as both the alpha and statistical significance increase monotonically along the OS quintiles. Our inferences remains unchanged when we skip a day between portfolio formation and return calculation, as shown in Table A2 of the Online Appendix. Collectively, these results reject the notion that market makers' delays in updating the prices of options leads to return predictability associated with $VWKS$.

4.2 Regression analysis

To further probe our univariate results, we examine the relation between $VWKS$ and subsequent underlying returns in a multiple regression setting while adopting Fama-MacBeth's (1973) estimation approach. To allow for the possibility that the price impact of $VWKS$ extends over multiple days, instead of the daily $VWKS$, we use the 5-day moving average of $VWKS$ ($VWKS\_MA5$) as the explanatory variable of interest[9] in the following model specification:

$$AQRET_{i,t} = \alpha + \beta VWKS\_MA5_{i,t-1} + \theta X\_MA5_{i,t-1} + \epsilon, \tag{3}$$

where $AQRET_{i,t}$ is the risk-adjusted mid quote return based on Fama and French (2015) and a momentum factors, and $X\_MA5_{i,t-1}$ is the set of 5-day moving averages of all the control variables, calculated similar to $VWKS\_MA5_{i,t-1}$. In these tests, we focus on risk-adjusted returns because the hypothesized link between $VWKS$ and subsequent underlying

[9]We decide to use a 5-day window based on the univariate portfolio results in Figure 1, which show predictability in underlying returns associated with $VWKS$ for up to 5 trading days after the portfolio formation date. Using moving averages instead of individual daily lags has at least two advantages. First, it allows us to assess the cumulative effect of each predictor over longer horizons without resorting to an F-test. Second, it makes the tables easier to present. However, we obtain very similar results when we replace the 5-day moving average with five separate variables corresponding the five lags in the moving average. The results of this analysis are available in Table A3 of the Online Appendix.

returns arises from private information, which should be reflected in the idiosyncratic component of returns. As before, we use mid quote returns to bypass concerns about the bid-ask bounce in daily returns. The set of control variables includes all of the known options market-based (PC, OS, DEV, $SKEW$, $IVOL$, $DCIVOL$, $DPIVOL$, $VOLVOL$) as well as the stock market-based predictors ($AQRET$, $SPREAD$, $TURN$, BM, $IDIOVOL$, $SIZE$). Table 5 reports the model estimates and t-statistics based on standard errors adjusted for serial correlations, up to eight lags (Newey and West (1987)).

Column (1) in Table 5 reports estimates from a simple regression of $AQRET$ on $VWKS\_MA5$, which provides a baseline to assess the stand-alone pricing effects of $VWKS$. The estimated coefficient is 0.584 with a t-statistic of 15.26. Consistent with the univariate results from sorting on daily values of $VWKS$, the evidence in Column (1) suggests the predictability of returns associated with $VWKS$ lasts up to a trading week. The specification reported in Column (2) includes the other known return predictors from the options market. In this specification, the coefficient estimate on $VWKS\_MA5$ remains positive, 0.461, and statistically significant, with a t-statistic of 13.2. Thus, although some of $VWKS$' explanatory power (21%) is absorbed by the other factors, the pricing effects of $VWKS$ remain economically large. The results for the other controls are mostly in line with the earlier univariate results. In Column (3), we further augment the model specification by including stock liquidity (past returns, bid-ask spreads, turnover ratios), as control variables. While some of the explanatory power of $VWKS\_MA5$ is further absorbed (approximately 39%), the relation between $VWKS$ and subsequent underlying returns remains economically large, 0.354, and statistically significant, with a t-statistic of 10.66. Moreover, consistent with prior studies, we find evidence of return reversal as well as positive pricing effects from both bid-ask spreads and turnover. The results are nearly identical in Column (4), where we control for firm specific characteristics, including book-to-market ratio (BM) as a proxy to leverage, firm's idiosyncratic volatility ($IdioVol$), logarithm of the market capitalization ($SIZE$), and stock order imbalance (OIB).

Overall, in line with the univariate results, the evidence in Table 5 supports the prediction stemming from Hypothesis 1 that the variation in $VWKS$ systematically explains (i.e., predicts) the variation in subsequent price changes of the underlying stock.

4.3 Robustness tests

To assess the robustness of our baseline inferences, we conduct a battery of additional tests. Table 6 summarizes the results of these tests. To begin, in Column (1), we repeat our tests after replacing mid quote risk-adjusted returns ($AQRET$) with their raw equivalent ($QRET$). Given the high correlation between $QRET$ and $AQRET$, it is perhaps unsurprising that the results of this analysis are very similar to those reported in Column (4) of Table 5.

[Table 6 about here]

Next, in Column (2), we repeat our analysis while using an alternative measure for the center of options trading volume mass along strike prices. Specifically, we use a log-transformation of our main measure defined as follows:

$$VWLNKS_{i,t} = \frac{\sum_{j=1}^{n} volume_{i,t,j}(log(K_{i,t,j}) - log(S_{i,t}))}{\sum_{j=1}^{n} volume_{i,t,j}}. \tag{4}$$

This transformation reduces the impact of potential outliers that may lead to excessively high K/S ratios, which may be a concern for our main measure, $VWKS$. Similar to our baseline analysis, we use the 5-day moving average of this alternative measure, $VWLNKS\_MA5_{i,t-1}$, as the main variable of interest in our specification. In line with the baseline evidence, the coefficient estimate on $VWLNKS\_MA5$ in Column (2) is positive, 0.323, and statistically significant at a 1% probability level, with a t-statistic of 9.44.

Option *moneyness*, which KS measures, is closely related to option *delta*, which reflects the option time value in addition to its moneyness. As such, option *delta* should be at least as important to informed options traders, who we conjecture affect the distribution of options volume across the various contracts available. Therefore, in Column (3) of Table 6, we replace our baseline measure with the center of options volume mass based on option *delta*,

$$VWDELTA_{i,t} = \frac{\sum_{j=1}^{n} volume_{i,t,j} DELTA_{i,t,j}}{\sum_{j=1}^{n} volume_{i,t,j}}. \tag{5}$$

Unlike KS, *delta* is signed, negative for put options and positive for call options. To make the measures comparable, we add one to put *delta* while keeping call *delta* the same in Equation (5). This adjustment essentially transforms put delta volume to call delta volume based on the stylized fact that customers' net demands for call and put options have opposite signs at the same strike price. Given that strike prices and call option *delta* are inversely related, the logic of our arguments implies that a higher $VWDELTA$ predicts lower future underlying stock returns. As shown in Column (3) of Table 6, consistent with the main results using $VWKS$, we find that higher $VWDELTA\_MA5$ predicts lower subsequent stock returns, with a coefficient estimate of -0.089 and a t-statistic of -5.93. Thus, whether we focus on the intrinsic value alone or also account for the time value, the evidence lines up with our main prediction that the distribution of options volume across available contracts on a stock moves in the direction of future underlying price changes.

Although we control for lagged returns in all of our tests, some concerns may remain about a mechanical correlation between $VWKS$ and subsequent underlying returns. If the underlying stock price drops by a small magnitude without changing the nature of moneyness of any option contract (e.g. from OTM to ATM), the distribution of options volume across K's may not change, resulting in mechanical increase in $VWKS$. Hence, one might question whether negative serial correlations in stock returns might explain the documented relation between $VWKS$ and subsequent underlying returns. To address this concern, in addition to controlling for lagged returns, we redefine the center of options volume mass, $VWKLS$, to explicitly remove any potential daily return reversal effect:

$$VWKLS_{i,t} = \frac{\sum_{j=1}^{n} volume_{i,t,j}(\frac{K_{i,t,j}}{S_{i,t-1}} - 1)}{\sum_{j=1}^{n} volume_{i,t,j}}. \tag{6}$$

Column (4) of Table 5 reports the results we obtain after replacing S_t with the lagged price S_{t-1} to ensure that the dynamics of $VWKS$ are not affected by contemporaneous stock price movements. Consistent with the baseline evidence, the average slope coefficient of $VWKLS\_MA5$ is positive, 0.143, and statistically significant, with a t-statistic of 4.11. Thus, it seems unlikely that the signal embedded in $VWKS$ about subsequent underlying returns is a spurious result of short-term return reversals.

Overall, the results of our robustness tests all point in the same direction. Independent of how we measure returns or $VWKS$ and whether we use option *delta* or KS to identify the location of the options volume distribution, we consistently find that variation in the distribution of options volume predicts the variation in subsequent returns, in line with informed options traders affecting the center of options volume mass along the continuum of contracts.[10]

4.4 The role of information asymmetry and arbitrage costs

Having established that $VWKS$ is a strong and robust predictor of subsequent underlying returns, we now turn our attention to the empirical evidence pertaining to Hypothesis 2.

[10]As a matter of fact, we performed various other tests in addition to those discussed here. Tables A4 to A9 of the Online Appendix report those results, which we do not discuss in detail for sake of brevity. This analysis includes testing our main hypothesis in the time-series as opposed to the cross-section of stocks, analyzing call separately from put options and positive separately from negative underlying stock returns, investigating non-linear effects, and separating the pricing effects of $VWKS$'s lagged levels versus innovations. Moreover, we zoomed in on M&A's announcements to test whether $VWKS$ contains information about impending but yet to be disclosed deals. Although these tests may be interesting in their own right, the most important takeaway for our purposes is that all of the resulting evidence supports our baseline inferences. Namely, we consistently find that there is yet-to-be-priced information about the underlying embedded in the location of the trading volume mass along the continuum of available option contracts written on a single stock. We refer interested readers to the Online Appendix for further details.

The corresponding tests are designed to ascertain whether the relation between $VWKS$ and subsequent returns depends on the degree of information asymmetry or arbitrage costs that characterize the underlying stock.

As discussed, we use four proxies for information asymmetry (firm size by market capitalization, number of analysts following the stock, fraction of institutional ownership, and probability of informed trading (PIN) of Easley, Kiefer, O'Hara, and Paperman (1996)) and four proxies for arbitrage costs (Amihud's (2002) illiquidity measure, relative bid-ask spread, idiosyncratic volatility, and sample time period). For each proxy - except the time period, we sort the sample into terciles every day and repeat our full-specification Fama-MacBeth (1973) regressions separately for the bottom and top terciles. For the subperiod analysis, we instead break the sample into halves. Table 7 reports the coefficient estimates that we obtain for $VWKS\_MA5$ in each subsample as well as the differences between the coefficient estimates across the low and high subsamples based on each of the aforementioned proxies.

[Table 7 about here]

We begin by examining whether and how the pricing effects of $VWKS$ vary with proxies of asymmetry in the underlying stock's information environment. In Panel A of Table 7, we examine the effects of $VWKS\_MA5$ conditional on firm size. The evidence shows that the relation between $VWKS$ and subsequent returns is positive, 0.482 and 0.292, and significant, with t-statistics of 10.87 and 5.6, for both small- and large-cap stocks, respectively. Although the predictability of returns associated with $VWKS$ is not confined to small stocks, the results support Hypothesis 2 in that the estimated effects are approximately 70% larger for small- than for large-cap stocks and this difference is significant at conventional levels, with a t-statistic of 3.01. In Panel B, we segment the sample by the number of equity analysts covering the stock. As in the case of size, we find that the estimated coefficient on $VWKS\_MA5$ is positive and statistically significant whether the stock analyst following is limited or broad. Moreover, in line with Hypothesis 2, a paucity of equity analysts following the firm is typically associated with larger pricing effects of $VWKS$. However, the effect in the *low* subsample is only about a quarter larger and the difference is not statistically significant at conventional probability levels.

When we examine the subsamples based on institutional ownership (Panel C) and PIN (Panel D), we obtain results that are similar to those for size in Panel A, which support Hypothesis 2. Specifically, although there is evidence of return predictability across all subsamples, the pricing effects of $VWKS$ are significantly larger when information asymmetries surrounding underlying stocks are likely more severe, as we expect to be the case when institutional ownership is low or PIN is high. Taken together, the evidence in Panels A-D of Table 7 lends support to Hypothesis 2 in that the signal embedded in $VWKS$ is more strongly linked to future underlying price changes when private information is more likely to play a role in the pricing of the underlying.

The remaining panels (E-H) of Table 7 present the results of the analysis based on proxies for arbitrage costs. Panel E reports the estimated pricing effects of $VWKS$ for the extreme terciles of stocks based on Amihud (2002) illiquidity. Similar to the analysis for proxies of information asymmetry, we find that the relation between $VWKS$ and subsequent underlying returns is positive, 0.245 and 0.498, and significant, with t-statistics of 4.53 and 10.97, for both liquid and illiquid stocks, respectively. This evidence supports Hypothesis 2 in that the pricing effects of $VWKS$ are approximately 50% larger for harder to arbitrage (i.e., less liquid) stocks and the difference across subsamples is statistically significant at conventional probability levels.

When we repeat the analysis using the other three proxies of arbitrage costs (bid-ask spreads in Panel F, idiosyncratic volatility in Panel G, and sample period in Panel H), we obtain generally similar results. Specifically, we find that $VWKS$ systematically predicts subsequent returns in all of the subsamples. However, relative to easier to arbitrage stocks, the estimated coefficients are consistently larger when arbitrage costs are likely higher: over

1.8% for high spread stocks (Panel F); over 200% for high idiosyncratic volatility stocks (Panel G); and over 37% for the first half of the sample (Panel H). Moreover, except for the subsamples based on relative bid-ask spread, the differences between subsamples are statistically significant. Overall, the evidence in Panels E-H of Table 7 supports the notion that the signal embedded in $VWKS$ about subsequent underlying returns is stronger when the costs of arbitrage for the underlying stock are likely to be higher.

4.5 $VWKS$ and the flow of corporate news

To establish a direct link between $VWKS$ and information flow, we classify trading days into *event* and *non-event days*. In doing so, we follow two complementary approaches. First, similar to prior studies, we use the filing of an 8-K in the SEC Analytics Suite database as indicative of the occurrence of a material event that the firm must disclose - as per rules governing these filings. We further segment 8-K filing dates into *scheduled* and *unscheduled* event days. Specifically, we classify as scheduled event days those corresponding to earnings announcements identified in the IBES database, which researchers routinely associate with arrival of information however anticipated. The dates of all other 8-K filings are instead classified as unscheduled event days.

We complement the set of event days based on 8-K filings with trading days during which there are large underlying price jumps without a corresponding 8-K filing. These are days when an event must occur that leads to a large stock price change without triggering 8-K filing requirements. In particular, if the underlying (absolute) risk-adjusted return is 10% or higher as in Savor (2012) or two standard deviations away from its mean as in Boehmer and Wu (2013), we classify the date as an event day. We further differentiate between *transitory* and *permanent* price jumps. Transitory price jumps ($tranjump$) are those that completely revert within five trading days after the jump, while permanent jumps ($permjump$) are all of the others. While permanent price jumps are likely associated with the arrival of fundamental information about the underlying stock, there are various events that may lead to transitory jumps, such as extreme liquidity shocks or manipulation. Whatever the reason, however, it is unlikely that transitory price changes are driven by the arrival of fundamental information, which provides a very valuable opportunity to conduct a placebo test for our Hypotheses 3 and 4.

If the underlying risk-adjusted return during an event day is positive (negative), we classify the event as positive (negative). Using this classification, we construct a series of categorical variables, $EVENT_{t+i}$, which takes value 1 or -1 on event day $t+i$ depending on the sign of announcement return on day t, and zero otherwise. We use this daily measure of signed information flow to test whether $VWKS$ exhibits abnormal behavior ahead of news arrival. In particular, we estimate the following pooled cross-sectional model including stock and calendar-week fixed effects:

$$VWKS_{j,t} = \alpha + \sum_{i=-5}^{5} \beta^i EVENT_{j,t+i} + \theta_j + \eta_w + \epsilon, \tag{7}$$

where θ_j and η_w are the stock and calendar-week fixed effects. For each event type, Columns (1-4) of Table 8 report the model coefficient estimates times 100 and t-statistics based on standard errors clustered by firm.

[Table 8 about here]

Table 8 shows that across all types of event dates we identify, there is a significant negative change in $VWKS$ on day t, on average. Because we assign the value of event variables based on the sign of the announcement return, the negative coefficients on $EVENT_t$ indicate that $VWKS$ reduces on positive announcement days and increases on negative announcement days. This result is consistent with options traders closing positions to take profits upon arrival of public news. Moreover, because we classify the events using announcement returns, there is a potential mechanical effect stemming from stock price changes. After the event day, we find that $VWKS$ continues to be significantly lower than average in the five trading days following events corresponding to 8-K filings and permanent price jumps, whereas it reverses course to become positive and significant in the case of transitory price jumps.

While the post-event behavior of $VWKS$ may be interesting in its own right, it is the remaining evidence in Table 8 that speaks directly to Hypothesis 3. In particular, the estimated coefficients on the *future* information flow indicators ($EVENT_{t-5}$ to $EVENT_{t-1}$) identify whether there is a systematic association between variation in $VWKS$ and future information arrival, which is the premise of our arguments. For any event type likely associated with fundamental information arrival in Columns (1-3), we find strong and robust evidence that the distribution of options volume along moneyness of available contracts systematically anticipates the events during each of the preceding five trading days. For example, the estimates for the earnings announcement events, Column (1), imply that daily $VWKS$ is abnormally high and increasingly so as the pre-event trading week progresses, with estimates from 0.137 to 0.273 as one moves from five to one day before the event, respectively. In addition to being statistically significant, the estimated effects are economically large, amounting to between 6 and 17 percent of $VWKS$' sample mean (0.018). By comparison, although the estimates remain large and statistically significant, their magnitude is smaller for *Unscheduled* news events in Column (2) relative to *Scheduled* ones in Column (1). Moreover, the run-up before unscheduled events only becomes statistically significant three days before the actual announcement while the run-up is already significant five days before scheduled announcements. Permanent price jumps unrelated to 8-K filings have the largest and most significant abnormal run-ups in $VWKS$. The results in the first three columns of Table 8 provide strong support for the prediction that $VWKS$ would increase (decrease) with informed options traders' anticipation of the subsequent arrival of fundamental positive (negative) news.

As previously discussed, transitory price jumps provide a valuable opportunity to conduct a placebo test of our main predictions on the effects of the underlying information flow. In particular, if transitory underlying price jumps are *not* the result of fundamental news, then we should find that $VWKS$ does *not* anticipate such events. Column (4) of Table 8 reports the results of this placebo test of our Hypothesis 3. Indeed, we find no evidence that the variation in $VWKS$ anticipates transitory price jumps in the right direction ahead of the event, although its behavior lines up with other event types on the event day or the following day and reverses thereafter. Thus, we cannot reject that investors who trade options on advanced knowledge of impending news (cannot and) do not anticipate price changes unrelated to the flow of fundamental information about the underlying. If nothing else, this (lack of) evidence in Column (4) rules out explanations of our findings based on stock or option market microstructure mechanisms, if the latter are independent of the underlying information flow.

4.6 Price sensitivity around corporate events

Given the link between underlying information flow and $VWKS$, we next examine whether the baseline relation between $VWKS$ and subsequent stock returns varies with the underlying information flow. In particular, following Hypothesis 4, we test whether the predictive power of $VWKS$ increases ahead of information events. To conduct these tests, we augment our baseline model specifications as follows:

$$\begin{aligned} AQRET_{i,t} = \alpha + \beta \cdot VWKS\_MA5_{i,t-1} + \gamma \cdot EventDummy_{i,t} + \\ \delta \cdot VWKS\_MA5_{i,t-1} \cdot EventDummy_{i,t} + \theta X\_MA5_{i,t-1} + \epsilon \end{aligned} \tag{8}$$

where the $EventDummy$ varies by event type. For earnings announcements, for example, the dummy $SCHEDULED$ equals one when there is an earnings announcement on day t, and zero otherwise. We code similarly the indicators for other event types (i.e., $UNSCHEDULED$, $PERMJUMP$, and $TRANJUMP$). Table 9 reports Fama-MacBeth (1973) estimates of the coefficients with t-statistics adjusted for autocorrelation.

[Table 9 about here]

The evidence in the table confirms our baseline evidence, in that we find a positive relation between $VWKS$ and subsequent underlying returns. Moreover, in line with Hypothesis 4, we also find that the underlying pricing effects associated with $VWKS$ depend on the dynamics of news about the stock. In particular, across all relevant event types, we find that the relation between $VWKS$ and underlying returns becomes stronger when they are associated with the arrival of new value relevant information. However, while the incremental pricing effects are statistically significant for unscheduled news, Column (2), and large permanent price jumps, Column (3), the effect is not significantly different from zero for earnings announcements, Column (1). This may not be all that surprising if, given the anticipated nature of earnings announcements, the underlying stock prices begin reflecting the signal embedded in $VWKS$ ahead of the upcoming news.

The magnitude of the incremental effects associated with the unanticipated arrival of information are notable. In particular, the estimated pricing effects of $VWKS$ for unscheduled news events, with a coefficient of 2.924, are roughly ten times larger than on other days, 0.254. Similarly, in the case of permanent price jump events, the effects are almost three times larger on news days, 0.592, compared to other days, 0.212. Column (4) reports the results of our placebo test exploiting transitory price jumps. In line with our expectations and the evidence in the prior table, we find no evidence that days ahead of transitory jumps are any different from a typical non-event day. Thus, it seems unlikely that our baseline results might be explained by microstructure effects unrelated to the arrival of fundamental information.

5 Conclusion

We argue that options trading by informed investors has a systematic impact on the distribution of options volume across available contracts on a single stock. In particular, we propose that option moneyness, as captured by the strike-to-spot price ratio (KS) of a contract, is a key element of an informed trader's optimal strategy. As such, we conjecture that the center of options volume mass along the continuum of available KS (i.e., $VWKS$) contains a valuable signal about future underlying returns.

The evidence is largely consistent with the tenets of our main conjecture. We find that a daily rebalanced investment strategy based on $VWKS$ generates large annualized abnormal returns, over 40%, during the past 21 years. Such abnormal return is persistent without subsequent reversals. Tests based on double sorted portfolios or multiple regression analysis, which account for other known stock return predictors yield similar results. The predictability is stronger when the options market is active. Thus, it appears that the signal embedded in $VWKS$ about future underlying returns stems from an information rather than a liquidity channel. The baseline evidence is robust to using alternative measures of the center of options volume mass or underlying returns. Moreover, the results from a battery of additional tests all point in the direction of $VWKS$ containing valuable information about future returns. Consistent with $VWKS$ reflecting informed options traders' activities, we find that the pricing effects of $VWKS$ are larger for stocks characterized by higher levels of information asymmetry or higher arbitrage costs. In support of a direct link between options trading and the underlying information flow, we find that $VWKS$ varies systematically with the flow of future news about the underlying stock. Correspondingly, we also find that the signal embedded in $VWKS$ about subsequent underlying returns is significantly stronger ahead of impending news about the stock fundamental value. The results of placebo tests that we conduct using temporary price jumps further strengthen this conclusion, by ruling out potential microstructure explanations that are independent of the underlying information flow.

Overall, in light of the collective evidence presented, we conclude that $VWKS$ embeds valuable fundamental information about the underlying stock as a result of informed trading in options that anticipates the underlying flow of news. In future research, it might be interesting to examine the impact of $VWKS$ on options implied volatility curves. Moreover, while we focus on KS, there are other features of option contracts that would be interesting to examine along similar lines. For example, examining the distribution of options volume along available contract maturities might prove to be a fruitful line of investigation.

Appendix A

In this appendix, we describe details of variable construction used in our analysis.

- PC: the put-call ratio, $log((1 + total\_put\_volume)/(1 + total\_call\_volume))$.
- OS: the option to stock volume ratio, $log((1+total\_option\_volume)/(1+stock\_volume))$. In calculating PC and OS, volumes are measured in number of shares traded.
- DEV: the deviation from put-call parity, the average difference of implied volatilities between call and put options across all option pairs with the same strike price and maturity.
- $SKEW$: the implied skewness, the difference between the implied volatilities of out-of-the-money puts (strike-to-price ratio lower than 0.95 but higher than 0.80) and at-the-money calls.
- $IVOL$: the options-implied volatility, the average implied volatility of at-the-money call and put options.
- $DCIVOL$: the first difference of at-the-money call options-implied volatility.
- $DPIVOL$: the first difference of at-the-money put options-implied volatility.
- $VOLVOL$: the standard deviation of implied volatility of at-the-money options in past 21 trading days.
- $SPREAD$: the percentage bid-ask spread calculated as the ask minus bid divided by the midpoint of the bid and ask times 100.
- $TURN$: the turnover ratio calculated as the total trading volume over the number of shares outstanding times 100.
- $QRET$:mid quote returns calculated using closing bid-ask prices and adjusted for stock splits and dividends.

- $AQRET$: the risk adjusted mid quote return based on Fama and French (1993), liquidity, and momentum factors.
- RET: the raw return from CRSP.
- $ARET$: the risk adjusted raw return based on Fama and French (2015) and momentum factors.
- BM: book-to-market ratio, total equity/market capitalization.
- $IDIOVOL$: stock's idiosyncratic volatility with respect to Fama and French (2015) and momentum factors.
- $SIZE$: the underlying firms' logarithm of market capitalization.
- OIB: dollars bought minus dollars sold all divided by the market capitalization with trades signed by the Lee and Ready (1991) algorithm.
- $NetBuyISE\_Delta$: net delta volume purchased by options traders at the International Securities Exchange (ISE) on the same stock.
- $NetBuyISE\_Gamma$: net gamma volume purchased by options traders at the ISE on the same stock.
- $NetBuyISE\_Vega$: net vega volume purchased by options traders at the ISE on the same stock.
- VW_OPTRET: the volume-weighted average of options return.

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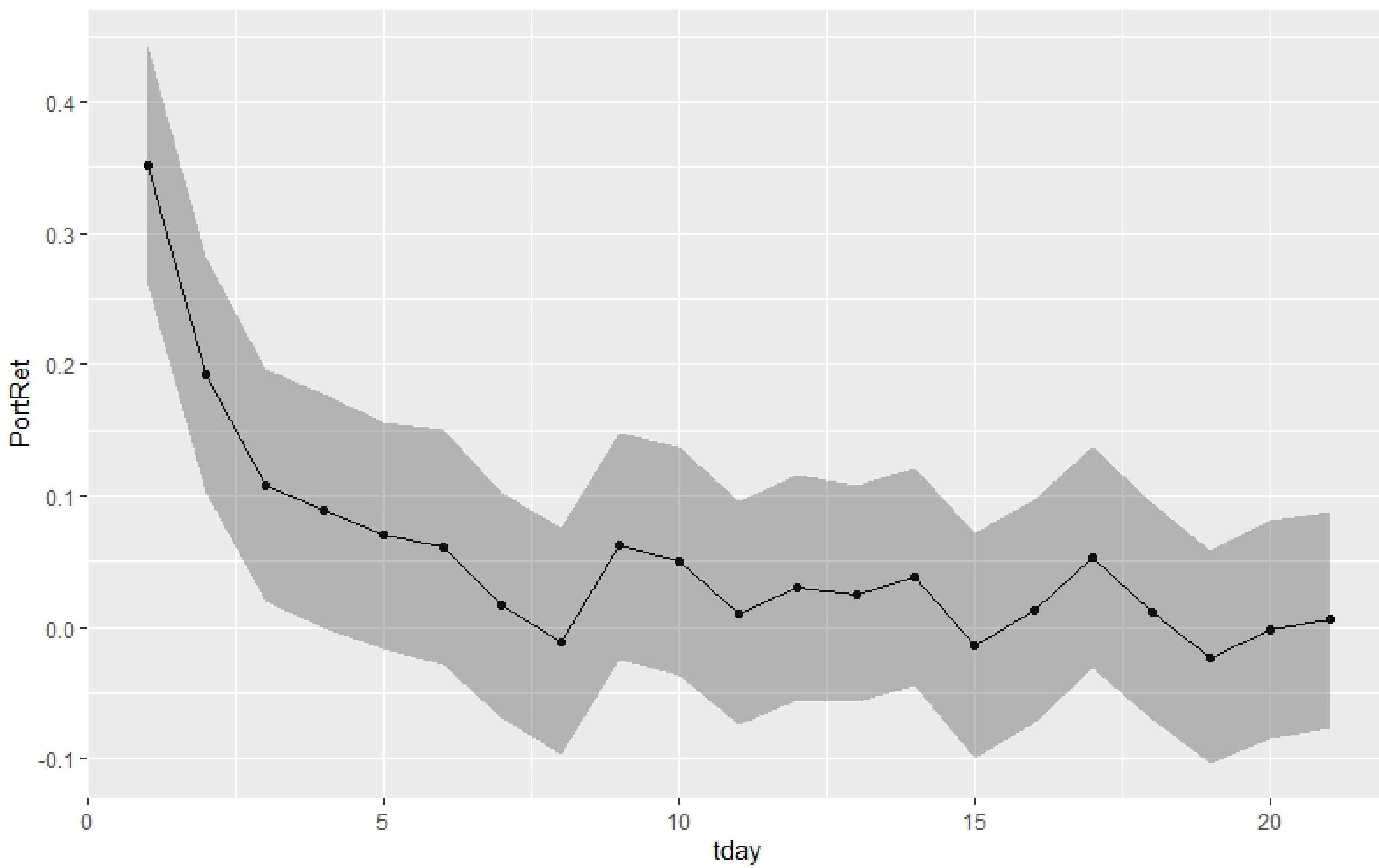

Figure 1: $VWKS$ sorted portfolio alpha

This figure plots the daily alphas (in basis points) of value-weighted long-short portfolio of the $VWKS$ strategy based on Fama-French (2015) and momentum factors on the next i^{th} day ($i = 1, 2, ...21$) after portfolio formation with the weight being a stock's market capitalization, and the 95% confidence intervals of alphas.

Table 1: Summary statistics

This table reports summary statistics of the main variables in the analysis between 1996 and 2016. We obtain daily stock and options data from CRSP and OptionMetrics for stocks with CRSP security code of 10 and 11, excluding those with prices below \$5. We also require the stock to have information in Compustat and NYSE TAQ databases to be included in the sample. $VWKS$ is the volume-weighted average KS minus one across all option contracts on the same stock, whereas KS is the ratio of option strike price and underlying stock price. PC is the put-call ratio, calculated as the $log((1 + total\_put\_volume)/(1 + total\_call\_volume))$. OS is the option to stock volume ratio calculated as $log((1 + total\_option\_volume)/(1 + stock\_volume))$. In calculating PC and OS, volumes are measured in number of shares traded. DEV is the deviation from put-call parity, calculated as the average difference of implied volatilities between call and put options across all option pairs with the same strike price and maturity. $SKEW$ is the implied skewness, calculated as the difference between the implied volatilities of out-of-the-money puts (strike-to-price ratio lower than 0.95 but higher than 0.80) and at-the-money calls. $IVOL$ is the options-implied volatility, calculated as the average implied volatility of at-the-money call and put options. $DCIVOL$ is the first difference of call options-implied volatility. $DPIVOL$ is the first difference of put options-implied volatility. $VOLVOL$ is the standard deviation of implied volatility of at-the-money options. Except DEV, implied volatilities are from OptionMetrics' standardized implied volatility surface with 30-day maturity. $SPREAD$ is the percentage bid-ask spread calculated as the ask minus bid divided by the midpoint of the bid and ask times 100. $TURN$ is the turnover ratio calculated as the total trading volume over the number of shares outstanding times 100. $QRET$ is mid quote returns calculated using closing bid-ask prices and adjusted for stock splits and dividends. $AQRET$ is the risk adjusted mid quote return based on Fama and French (2015) and momentum factors. BM is book-to-market ratio. $IDIOVOL$ is stock's idiosyncratic volatility. $SIZE$ is the underlying firms' logarithm of market capitalization. OIB is dollars bought minus dollars sold all divided by the market capitalization with trades signed by the Lee and Ready (1991) algorithm. All variables except $QRET$ and $AQRET$ are winsorized at the 0.5^{th} and 99.5^{th} percentiles.

Variable	N	Mean	Std Dev	Minimum	Maximum
$VWKS$	6789851	0.018	0.105	-0.531	2.687
PC	6671596	-1.687	3.856	-12.054	9.925
OS	6671596	-5.752	3.571	-15.213	-0.461
DEV	6669185	-0.007	0.081	-2.208	1.263
$SKEW$	6669185	0.032	0.107	-1.327	2.228
$IVOL$	6669185	0.459	0.225	0.071	2.280
$DCIVOL$	6661905	0.000	0.072	-1.316	1.591
$DPIVOL$	6661905	0.000	0.072	-1.707	1.574
$VOLVOL$	6563155	0.043	0.049	0.001	0.701
$SPREAD$	6576974	1.114	1.67	0.005	57.072
$TURN$	6789851	5.274	5.399	0.091	175.114
$QRET$	6789851	0.001	0.032	-0.814	4.821
$AQRET$	6789851	0.000	0.027	-1.061	4.781
BM	6409071	0.477	0.38	-1.244	4.472
$IDIOVOL$	6765395	0.026	0.017	0.000	0.217
$SIZE$	6789580	14.271	1.524	10.795	19.861
OIB	6789851	0.002	0.090	-1.000	1.000

Table 2: Determinants of $VWKS$

This table reports time-series averages of daily cross-sectional coefficients for the following model in the sample of stocks with options listed on the International Securities Exchange (ISE) between 2006 and 2014:

$$VWKS_{i,t} = \alpha + \beta NetBuyISE\_Delta_{i,t} + \theta X_{i,t-1} + \epsilon,$$

where $NetBuyISE\_Delta_{i,t}$ is same-day net delta volume purchased by options traders at ISE on day t for firm i, and the vector $X_{i,t-1}$ includes the net gamma volume purchased at the ISE ($NetBuyISE\_Gamma$), the net vega volume purchased at the ISE ($NetBuyISE\_Vega$), the underlying stock order imbalance (OIB), stock return (RET), and the volume-weighted average options return (VW_OPTRET). OIB is total buyer initiated volume minus total seller initiated volume scaled by the sum of the two with trade directions estimated using the Lee and Ready (1991) algorithm without any quote lag. In Columns (1) and (2), $VWKS$ is calculated using only option trades executed at the ISE. In Columns (3) and (4), $VWKS$ is calculated using option volumes from all the options exchanges in OptionMetrics. The t-statistics are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)
Intercept	0.088***	0.065***	0.025***	0.024***
	[8.82]	[8.71]	[13.36]	[15.36]
NetBuyISE_Delta	0.058***	0.047***	0.009***	0.008***
	[19.15]	[19.36]	[21.38]	[18.99]
NetBuyISE_Gamma		-0.002		-0.001
		[-1.30]		[-0.96]
NetBuyISE_Vega		0.002		0.001
		[1.18]		[0.76]
RET		-3.573***		-0.374***
		[-15.39]		[-36.21]
OIB		-0.106***		-0.015***
		[-6.49]		[-8.47]
VW_OPTRET		0.005***		0.003***
		[3.43]		[2.30]
adj. R^2	0.003	0.047	0.004	0.029
Obs per day	656	656	656	656

Table 3: Univariate portfolio sorts

In the merged sample of stocks in CRSP and OptionMetrics with priced above $5 between 1996 and 2016, we sort stocks into decile portfolios based on one of the options market signals at the end of each day. This table reports value-weighted average returns (in basis point) of the decile portfolios on the next day with the weight being a stock's market capitalization. Also reported are the average return differentials between the top and bottom decile portfolios as well as corresponding long-short portfolio alphas based on Fama-French (2015) and momentum factors. Stock returns are calculated using the midpoint of the bid and ask prices at market close adjusted for stock splits and dividends. All variables are the same as defined in Table 1. The t-statistics for mean return differentials and alpha's are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	VWKS	*PC*	*OS*	*DEV*	*SKEW*	*IVOL*	*DCIVOL*	*DPIVOL*	*VOLVOL*
Low	-4.020	5.413	5.181	0.263	10.860	1.659	0.060	3.855	3.119
2	0.171	1.766	3.429	0.835	7.776	3.252	0.723	2.522	3.051
3	2.014	5.118	4.535	0.212	6.609	4.231	2.731	4.151	2.719
4	3.743	6.505	4.827	1.677	4.765	4.714	2.685	3.534	3.910
5	3.642	5.420	5.073	1.574	4.164	5.221	3.060	4.072	4.480
6	4.891	2.989	4.623	4.307	3.929	4.770	3.684	3.326	3.522
7	5.566	1.619	3.998	6.058	2.261	6.312	4.155	4.562	4.045
8	6.896	3.422	4.507	7.237	1.394	5.771	5.021	3.285	4.795
9	6.923	2.185	3.792	10.127	1.677	7.247	6.342	3.756	6.159
High	9.378	0.917	2.599	13.813	-0.565	13.361	10.157	6.988	5.843
High-Low	13.398***	-4.497***	-2.582**	13.550***	-11.425***	11.702***	10.097***	3.132*	2.723
	[7.24]	[-6.88]	[-2.28]	[9.31]	[-6.20]	[3.23]	[5.56]	[1.77]	[1.04]
FF5 alpha	13.784***	-4.449***	-2.329**	13.926***	-11.432***	12.075***	10.443***	3.104*	2.999
	[7.45]	[-6.80]	[-2.05]	[9.56]	[-6.18]	[3.34]	[5.74]	[1.75]	[1.14]

Table 4: Bi-variate portfolio sorts

This table reports value-weighted average returns (in basis point) of daily rebalanced double-sorted quintile portfolios as well as return differentials between top and bottom $VWKS$ quintiles, and corresponding long-short portfolio alpha's based on Fama-French (2015) and momentum factors. Stock returns are calculated using the midpoint of the bid and ask prices at market close adjusted for stock splits and dividends. All variables are the same as defined in Table 1. To form portfolios, each day, we first sort all stocks into quintile portfolios based on a control variable - i.e., $QRET$ (Panel A), OS (Panel B), PC (Panel C), DEV (Panel D), $SKEW$ (Panel E), $IVOL$ (Panel F), $DCIVOL$ (Panel G), $DPIVOL$ (Panel H), and $VOLVOL$ (Panel I). Then, within each quintile, we further sort stocks into quintiles based on $VWKS$. The t-statistics for return differentials and alpha's are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

VWKS	low	2	3	4	high
			Panel A: QRET		
Low	1.545	0.970	0.008	-1.355	-6.061
2	5.832	4.264	2.261	1.995	0.085
3	4.156	5.517	3.383	3.785	4.567
4	8.940	4.677	4.913	5.931	6.735
High	10.554	6.336	6.283	7.384	10.352
High-Low	9.009***	5.367***	6.275***	8.739***	16.414***
	[3.93]	[3.16]	[4.30]	[5.62]	[8.11]
FF5 alpha	8.981***	5.169***	6.179***	8.729***	16.989***
	[3.91]	[3.05]	[4.24]	[5.63]	[8.39]
			Panel B: OS		
Low	5.178	3.984	2.040	-0.438	-4.146
2	4.641	4.321	4.037	2.857	2.874
3	4.378	4.023	4.796	5.937	5.432
4	4.596	5.007	6.503	6.726	6.595
High	4.226	7.116	9.323	10.340	7.665
High-Low	-0.952	3.132***	7.283***	10.778***	11.811***
	[-1.31]	[2.68]	[4.26]	[5.21]	[5.40]
FF5 alpha	-0.977	3.264***	7.584***	11.077***	11.987***
	[-1.34]	[2.80]	[4.43]	[5.35]	[5.49]

Table 4 (continued):

VWKS	low	2	3	4	high
			Panel C: PC		
Low	-3.339	-1.196	0.569	-1.410	0.375
2	5.449	6.079	3.239	3.621	1.926
3	5.025	8.716	4.595	4.490	1.998
4	6.623	8.540	5.879	3.929	3.046
High	6.969	10.641	9.898	2.859	1.889
High-Low	10.308***	11.838***	9.329***	4.269***	1.514
	[7.55]	[5.85]	[4.46]	[2.66]	[0.95]
FF5 alpha	10.330***	12.351***	9.464***	4.329***	1.588
	[7.56]	[6.11]	[4.52]	[2.69]	[1.00]
			Panel D: DEV		
Low	-2.056	-2.097	-1.508	1.162	4.692
2	-0.578	1.729	1.013	6.475	10.039
3	2.385	3.209	3.325	6.290	10.572
4	2.727	2.201	5.768	7.327	13.808
High	2.876	2.555	7.004	9.809	16.420
High-Low	4.933**	4.653***	8.513***	8.647***	11.728***
	[2.47]	[2.63]	[5.03]	[4.79]	[5.40]
FF5 alpha	5.528***	4.692***	8.582***	8.751***	11.928***
	[2.77]	[2.66]	[5.07]	[4.84]	[5.49]
			Panel E: SKEW		
Low	5.427	0.127	-0.087	-0.857	-4.699
2	7.377	4.244	2.824	1.118	0.537
3	7.210	6.456	5.895	1.917	3.333
4	9.693	7.518	5.484	3.468	4.289
High	15.876	9.014	6.687	5.935	4.211
High-Low	10.449***	8.888***	6.774***	6.791***	8.910***
	[5.46]	[5.41]	[4.29]	[3.76]	[4.24]
FF5 alpha	10.906***	9.084***	6.957***	6.891***	8.853***
	[5.71]	[5.53]	[4.40]	[3.84]	[4.21]
			Panel F: IVOL		
Low	-2.204	1.159	0.534	-0.205	-1.957
2	1.663	2.756	2.866	3.576	7.743
3	2.166	5.231	2.894	6.751	10.584
4	4.589	6.876	6.423	6.494	13.847
High	4.937	5.079	8.488	9.351	20.950
High-Low	7.141***	3.921***	7.954***	9.556***	22.907***
	[8.51]	[3.10]	[4.52]	[4.36]	[8.68]
FF5 alpha	7.119***	3.903***	7.918***	9.477***	22.781***
	[8.50]	[3.09]	[4.50]	[4.33]	[8.64]

Table 4 (continued):

VWKS	low	2	3	4	high
		Panel G: DCIVOL			
Low	-2.646	-2.240	-0.324	0.323	3.054
2	0.673	1.136	3.166	4.123	6.776
3	2.555	4.251	4.109	5.033	5.604
4	1.757	5.365	5.133	6.349	12.072
High	4.774	5.693	6.477	7.863	16.304
High-Low	7.420***	7.933***	6.801***	7.539***	13.250***
	[3.61]	[4.93]	[4.49]	[4.34]	[5.31]
FF5 alpha	7.701***	8.179***	6.960***	7.497***	13.304***
	[3.75]	[5.09]	[4.61]	[4.31]	[5.33]
		Panel H: DPIVOL			
Low	-3.186	0.242	-0.539	-2.170	-0.888
2	3.222	2.072	3.534	3.745	3.438
3	5.811	4.324	3.294	5.836	5.511
4	6.002	5.011	6.383	5.617	7.481
High	7.326	7.332	5.580	6.402	12.922
High-Low	10.512***	7.091***	6.120***	8.572***	13.810***
	[4.96]	[4.26]	[4.01]	[4.89]	[5.76]
FF5 alpha	10.594***	7.173***	6.503***	8.681***	13.980***
	[5.00]	[4.31]	[4.26]	[4.96]	[5.82]
		Panel H: VOLVOL			
Low	-0.728	-0.993	0.178	-1.635	-0.740
2	2.576	2.717	3.156	3.631	5.293
3	4.149	4.488	5.496	3.773	4.041
4	4.739	6.076	5.722	7.889	8.900
High	6.516	5.274	5.073	8.339	14.783
High-Low	7.244***	6.268***	4.895***	9.974***	15.523***
	[6.73]	[4.69]	[2.92]	[4.85]	[6.20]
FF5 alpha	7.472***	6.470***	5.046***	9.941***	15.666***
	[6.94]	[4.85]	[3.01]	[4.83]	[6.26]

Table 5: Fama-MacBeth (1973) regressions

This table reports time-series averages of daily cross-sectional coefficients for the following model:

$$AQRET_{i,t} = \alpha + \beta VWKS\_MA5_{i,t-1} + \theta X\_MA5_{i,t-1} + \epsilon,$$

where $AQRET_{i,t}$ is the risk-adjusted mid quote stock return on day t for firm i, $VWKS\_MA5_{i,t-1}$ is the 5-day moving average (MA) of $VWKS$ measured on day $t-1$, and X_MA5 is a vector of 5-day moving averages measured on day $t-1$ for all the control variables. All variables are the same as defined in Table 1. The t-statistics are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)
Intercept	-0.017***	-0.107***	-0.197***	-0.424***
	[-6.25]	[-12.16]	[-12.14]	[-10.16]
VWKS_MA5	0.584***	0.461***	0.354***	0.334***
	[15.26]	[13.20]	[10.66]	[10.25]
PC_MA5		-0.003***	-0.005***	-0.006***
		[-4.43]	[-6.82]	[-8.40]
OS_MA5		-0.006***	-0.006***	-0.007***
		[-7.08]	[-8.19]	[-8.08]
DEV_MA5		0.111**	0.130***	0.133***
		[2.29]	[2.69]	[2.74]
SKEW_MA5		-0.409***	-0.386***	-0.382***
		[-13.97]	[-13.39]	[-13.35]
IVOL_MA5		0.115***	0.056***	0.104***
		[6.46]	[2.87]	[4.71]
DCIVOL_MA5		1.598***	1.137***	1.091***
		[10.14]	[7.44]	[7.19]
DPIVOL_MA5		0.354**	0.084	0.035
		[2.23]	[0.53]	[0.22]
VOLVOL_MA5		0.106	0.018	-0.031
		[1.64]	[0.27]	[-0.48]
AQRET_MA5			-2.784***	-2.818***
			[-10.43]	[-10.50]
SPREAD_MA5			0.136***	0.144***
			[8.12]	[8.68]
TURN_MA5			0.024***	0.024***
			[6.84]	[6.60]
BM_MA5				0.064***
				[11.88]
IdioVol_MA5				-0.102**
				[-2.21]
SIZE_MA5				0.012***
				[6.79]
OIB_MA5				1.415
				[0.62]
adj. R^2	0.003	0.014	0.023	0.028
Obs per day	1200	1200	1200	1200

Table 6: Robustness tests using alternative measures

This table reports Fama-MacBeth (1973) estimates for the model specification in Column (4) of Table 5 based on alternative measures of underlying returns or of the location of option volume mass. In Column (1), we report results using mid quote returns as the dependent variable instead of risk adjusted mid quote returns. In Column (2), we redefine $VWKS$ to use the difference between logarithms of the strike and spot prices instead of the strike-to-spot price ratio. In Column (3), we replace the strike-to-spot price ratio with option *delta* for calls and one plus *delta* for puts. In Column (4), we calculate $VWKS$ using lagged underlying price on the previous day instead of the spot price. The t-statistics are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)
Intercept	-0.378***	-0.430***	-0.341***	-0.299***
	[-6.97]	[-10.27]	[-7.77]	[-3.74]
VWKS_MA5	0.250***	0.323***	-0.089***	0.143***
	[6.92]	[9.44]	[-5.93]	[4.11]
PC_MA5	-0.009***	-0.006***	-0.010***	-0.003***
	[-10.79]	[-8.38]	[-11.89]	[-2.68]
OS_MA5	-0.006***	-0.006***	-0.010***	-0.010***
	[-6.80]	[-7.58]	[-9.53]	[-4.14]
DEV_MA5	0.114**	0.131***	0.141***	0.127
	[2.20]	[2.70]	[2.90]	[1.15]
SKEW_MA5	-0.462***	-0.386***	-0.409***	-0.255***
	[-13.94]	[-13.49]	[-14.15]	[-4.14]
IVOL_MA5	0.203***	0.115***	0.139***	0.119**
	[4.89]	[5.19]	[6.18]	[2.28]
DCIVOL_MA5	0.997***	1.088***	1.052***	0.365***
	[6.36]	[7.17]	[6.93]	[3.33]
DPIVOL_MA5	0.071	0.035	0.048	-0.12
	[0.43]	[0.22]	[0.31]	[-1.12]
VOLVOL_MA5	-0.003	-0.026	-0.043	-0.079
	[-0.04]	[-0.41]	[-0.67]	[-0.58]
AQRET_MA5	-2.364***	-2.846***	-3.053***	0.258
	[-8.12]	[-10.60]	[-11.30]	[1.12]
SPREAD_MA5	0.172***	0.145***	0.145***	0.073**
	[8.47]	[8.73]	[8.74]	[2.10]
TURN_MA5	0.028***	0.024***	0.020***	0.013*
	[6.68]	[6.69]	[5.33]	[1.88]
BM_MA5	0.033***	0.065***	0.068***	0.049***
	[4.30]	[12.04]	[12.37]	[3.93]
IdioVol_MA5	-0.078	-0.101**	-0.099**	-0.026
	[-1.64]	[-2.18]	[-2.14]	[-0.32]
SIZE_MA5	0.011***	0.013***	0.010***	0.008**
	[4.20]	[6.90]	[5.19]	[2.51]
OIB_MA5	-1.139	1.503	2.604	-0.043**
	[-0.50]	[0.63]	[1.09]	[-2.16]
adj. R^2	0.06	0.028	0.027	0.057
Obs per day	1200	1200	1200	1200

Table 7: Subsample analysis

This table reports Fama-MacBeth (1973) estimates of the model in Column (4) of Table 5 for various subsamples based on stocks characteristics. First, we sort stocks into terciles based on stock market capitalization (*Size*) in Panel A, number of analysts following the stock (*Analyst*) in Panel B, fraction of institutional ownership (*Ownership*) in Panel C, probability of informed trading (*PIN*) as in Easley, Kiefer, O'Hara, and Paperman (1996) in Panel D, illiquidity as in Amihud (2002) in Panel E, underlying bid-ask spreads (*Spread*) in Panel F, and idiosyncratic stock volatility (*Idio*) in Panel G. In Panel H, we divide the sample into two halves. Then, we estimate coefficients from the baseline specification in Column (4) of Table 5 for each extreme subsample. For brevity, the table only reports estimated coefficients on $VWKS\_MA5$ within each subsample as well as the difference in coefficient estimates across subsamples. The t-statistics are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	Panel A: *Size*			Panel B: *Analyst*		
	small	*large*	*small-large*	*low*	*high*	*low-high*
VWKS_MA5	0.482***	0.292***	0.190***	0.375***	0.287***	0.088
	[10.87]	[5.60]	[3.01]	[8.06]	[5.32]	[1.34]

	Panel C: *Ownership*			Panel D: *PIN*		
	low	*high*	*low-high*	*low*	*high*	*low-high*
VWKS_MA5	0.416***	0.274***	0.142***	0.255***	0.407***	-0.152***
	[7.60]	[5.87]	[2.18]	[4.38]	[8.75]	[-2.13]

	Panel E: *Illiquidity*			Panel F: *Spread*		
	low	*high*	*low-high*	*low*	*high*	*low-high*
VWKS_MA5	0.245***	0.498***	-0.253***	0.385***	0.378***	0.007
	[4.53]	[10.97]	[-3.80]	[8.58]	[8.41]	[0.11]

	Panel G: *Idio*			Panel H: *Year*		
	low	*high*	*low-high*	*early*	*late*	*early-late*
VWKS_MA5	0.122***	0.479***	-0.357***	0.409***	0.298***	0.111***
	[3.58]	[9.73]	[-6.33]	[8.40]	[6.02]	[2.66]

Table 8: Dynamics of $VWKS$ and underlying information flow

The table reports ordinary least squares estimates of the following pooled cross-sectional model:

$$VWKS_{j,t} = \alpha + \sum_{i=-5}^{5} \beta^i EVENT_{j,t+i} + \theta_j + \eta_w + \epsilon,$$

where $EVENT_{j,t+i}$ is 1 (-1) if for event day $t+i$ relative to an event with a positive (negative) risk-adjusted announcement return, and 0 otherwise. All specifications include firm and calendar-week fixed effects, θ and η. Column (1) reports results for the subsample of *Scheduled* news events, corresponding to earnings announcements. Column (2) reports results for *Unscheduled* news events, corresponding to 8-K filings not related to earnings news. Column (3) and (4) reports results for event days associated with price jumps (i.e., risk-adjusted return higher than 10% in absolute value as in Savor (2012) or two standard deviations away from its mean as in Boehmer and Wu (2013)) and no corresponding 8-K filing. $Tranjump$ in Column (4) refers to daily price jumps that completely revert within 5 trading days, whereas $Permjump$ refers to all of the others. The t-statistics are based on standard errors clustered by firm and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	(1) *Scheduled*	(2) *Unscheduled*	(3) *Permjump*	(4) *Tranjump*
EVENT_t-5	0.137**	0.023	0.272***	-0.1
	[2.22]	[0.79]	[8.38]	[-0.79]
EVENT_t-4	0.138**	0.017	0.354***	-0.402***
	[2.00]	[0.54]	[9.94]	[-2.90]
EVENT_t-3	0.115*	0.110***	0.422***	-0.790***
	[1.71]	[3.19]	[11.22]	[-5.35]
EVENT_t-2	0.288***	0.199***	0.656***	0.046
	[3.57]	[5.47]	[16.43]	[0.31]
EVENT_t-1	0.273***	0.239***	0.657***	-0.056
	[3.18]	[6.30]	[16.03]	[-0.34]
EVENT	-0.751***	-0.701***	-2.828***	-3.055***
	[-7.95]	[-17.84]	[-47.36]	[-17.36]
EVENT_t+1	-0.440***	-0.385***	-1.396***	-0.299*
	[-4.95]	[-10.27]	[-29.36]	[-1.92]
EVENT_t+2	-0.330***	-0.338***	-1.041***	0.810***
	[-3.92]	[-9.63]	[-24.56]	[5.47]
EVENT_t+3	-0.179**	-0.182***	-0.799***	0.888***
	[-2.15]	[-5.34]	[-19.94]	[5.74]
EVENT_t+4	-0.197***	-0.151***	-0.598***	0.987***
	[-2.61]	[-4.78]	[-15.52]	[6.91]
EVENT_t+5	-0.115*	-0.057*	-0.375***	0.702***
	[-1.72]	[-1.76]	[-11.58]	[5.52]
Calendar-Week FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
R^2	0.304	0.304	0.306	0.304
Obs	6714549	6714549	6714549	6714549

Table 9: Pricing effects of $VWKS$ conditional on underlying information flow

This table reports Fama-Macbeth (1973) estimates of the following model:

$$AQRET_t = \alpha + \beta \cdot VWKS\_MA5_{i,t-1} + \gamma \cdot EventDummy + \delta \cdot VWKS\_MA5_{i,t-1} \cdot EventDummy + \theta X\_MA5_{i,t-1} + \epsilon. \quad (9)$$

$EventDummy$ is either: a $SCHEDULED$ indicator that equals one when there is an earnings announcement on day t, and zero otherwise; or an $UNSCHEDULED$ indicator for 8-K filings unrelated to earnings news; or a $PERMJUMP$ indicator for permanent price jumps; or a $TRANJUMP$ indicator for transitory price jumps that completely revert within five days. All of the control variables from Column (4) in Table 5 are included in the specification but not reported for brevity. The t-statistics are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VWKS_MA5	0.253***	0.254***	0.212***	0.264***	0.230***
	[7.49]	[7.56]	[6.41]	[7.83]	[6.94]
SCHEDULED	0.027				0.03
	[0.77]				[0.84]
*KS*SCHEDULED*	4.103				4.118
	[0.73]				[0.73]
UNSCHEDULED		0.017			0.022
		[0.23]			[0.29]
*KS*UNSCHEDULED*		2.924*			2.953*
		[1.81]			[1.85]
PERMJUMP			0.326***		0.312***
			[27.54]		[26.73]
*KS*PERMJUMP*			0.592***		0.555***
			[3.25]		[3.05]
TRANJUMP				1.773***	1.757***
				[9.13]	[8.91]
*KS*TRANJUMP*				5.311	5.112
				[0.96]	[0.92]
Control	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.029	0.03	0.031	0.033	0.04
Obs per day	1200	1200	1200	1200	1200

Online Appendix: "Center of Volume Mass: Does Options Trading Predict Stock Returns?"

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1 Weekly portfolio analysis

Table A1 reports weekly rebalanced strategies with a week starting on Wednesday and ending on the coming Tuesday.

[Table A1 about here]

As a lower turnover and more practical strategy, a portfolio using high $VWKS$ decile minus low $VWKS$ decile as the trading signal has generated an average return of 38 basis points, or 20% annualized after adjusting for Fama-French (2015) and momentum factors. The $DCIVOL$ strategy generates a 26.9% annualized return with a t-statistic of 7.22, even better than its daily rebalanced strategy. The DEV strategy generates a 21.6% annualized return with a t-statistic of 7.48, followed by $DPIVOL$ with a 11.7% annualized return and a t-statistic of 3.28. Portfolio returns using PC and OS are not economically nor statistically significant in weekly rebalanced portfolios.

2 Daily double sorted portfolio analysis

We examine the daily profitability of the $VWKS$ strategy controlling for the effects from PC, OS, DEV, $SKEW$, $IVOL$, $DCIVOL$, $DPIVOL$, $VOLVOL$ and $QRET$ in a double sorting investment analysis. Table A2 presents portfolio alphas with respect to Fama French (2015) and momentum factors on the second day after portfolio formation.

[Table A2 about here]

In row $QRET$, the sample is first sorted into quintile portfolios based on $QRET$. Within each $QRET$ quintile, the subsample is further sorted into quintile portfolios by $VWKS$. Investment strategies are formed using high $VWKS$ quintile minus low $VWKS$ quintile and the returns are calculated using the market capitalization as weights. We report annualized alphas with Newey-West (1987) t-statistics. Similarly, we first sort the sample into quintile portfolios each day by OS, PC, DEV, $SKEW$, $IVOL$, $DCIVOL$, $DPIVOL$, and $VOLVOL$. Within each quintile, we further sorted the portfolio into quintile portfolios by $VWKS$.

Despite different control variables in every panel, 42 out of 45 $VWKS$ strategies generate statistically significant returns at the 10% level or better. In row $QRET$, the portfolio in the lowest quintile has an alpha of 7.67 basis points and a t-statistic of 3.52. The result indicates that the signal embedded in $VWKS$ is orthogonal to the one embedded in the past returns. In row OS, the $VWKS$ strategy in the highest OS quintile generates an average of 7.2 basis points return with a t-statistic of 4.88. All five $VWKS$ strategies in row PC performs well. The second PC quintile has an alpha of 8 basis points and a t-statistic of 4.03. The alphas in the highest quintile of DEV are 9.3 basis points. The portfolio in the highest quintile has an alpha of 8.7 basis points and a t-statistic of 4.16 in row $SKEW$, 17 basis points and a t-statistic of 6.43 in row $IVOL$, 10.7 basis points and a t-statistic of 4.76 in row $DCIVOL$, 12.87 basis points and a t-statistic of 5.6 in row $DPIVOL$, and 11.8 basis points and a t-statistic of 4.91 in row $VOLVOL$.

3 Regression analysis with daily lags

We estimate the following model in the cross section:

$$AQRET_{i,t+1} = \alpha + \sum_{l=1}^{5} \beta_l VWKS_{i,t-l} + \sum_{l=1}^{5} \theta_l X_{i,t-l} + \epsilon, \tag{1}$$

where the risk-adjusted weekly return, $AQRET_{i,t+1}$, is regressed on five lags of all the explanatory variables, including $VWKS$, PC, OS, DEV, $SKEW$, $IVOL$, $DCIVOL$, $DPIVOL$, $VOLVOL$, $ARET$, $SPREAD$, $TURN$, RET^2, BM, $IdioVol$, $SIZE$ and OIB. After obtaining a time series of the slope coefficients, we then examine the mean of these coefficients using Newey-West (1987) adjustment, allowing for autocorrelation structures. For ease of reporting, the returns are expressed as percentages.

[Table A3 about here]

The results are reported in Table A3. The first model presents the univariate regression results using one lag of $VWKS$. The average slope coefficient of $VWKS$ is 0.216, statistically significant at the 1% level (t-statistic = 10.54). Adding four more lags, the second model shows that the four lags of $VWKS$ are positive and significant at the 5% level and above. The third model controls for five lags of all return predictors from the options market, i.e. PC, OS, DEV, $SKEW$, $IVOL$, $DCIVOL$, $DPIVOL$, $VOLVOL$. Besides the fifth lag, all the other lags are positive and significant at the 5% level. After further controlling for $ARET$, $SPREAD$, $TURN$ and their lags in model [4], first, second, fourth and fifth lags of $VWKS$ are positive and significant at the 10% level or better. Model [5] presents the full model regression results. $VWKS$ has a coefficient of 0.083 with a t-statistic of 4.95 on the first lag. First, second, fourth and fifth lags are positive and significant at the 5% level or better.

4 Time series regression analysis

$VWKS$, its alternatives, and their 5-day MAs are significant at the 1% cross-sectionally, examined by Fama-Macbethe regression. In this subsection, we analyze them in the time series regressions in Table A4.

[Table A4 about here]

Panel A studies $VWKS$ and its alternative measures using the following equation:

$$AQRET_{i,t} = \alpha + \sum_{l=1}^{5} \beta_l VWKS_{i,t-l} + \sum_{l=1}^{5} \theta_l AQRET_{i,t-l} + \epsilon.$$

In the first model of the time series regression, we test the risk adjusted mid quote returns ($AQRET1$) regression results using one lag of $VWKS$. The average slope coefficient of 0.004, statistically significant at the 1% level (t-statistic = 24.57). The second model uses five lags of $VWKS$, all significant at the 1% level. The coefficient of the first lag in the second model is 0.002, with a t-statistic of 14.37. In the third regression, we reports five lags of $VWKS$ and $AQRET$.The fourth regression tests risk adjusted raw returns instead of risk adjusted mid quote returns, while the fifth regression tests the raw mid quote returns. All five lags of model [3], [4] and [5] are positive and significant at 1% level and above, and the coefficients of the first lag are 0.002, with a t-statistic of at least 10.95. The sixth model tests the log transformation of $VWKS$, $VWLNKS$, with regard to $AQRET1$. The first lag of $VWLNKS$ has an average slope of 0.020, significant at the 1% level (t-statistic = 11.34). The seventh model tests $VWDELTA$, the center of volume mass based on option *deltas*. All five lags are negative, of which the second, third and fourth lags are negative and significant at 1% level. The eighth model tests $VWKLS$ which replaces S_{t-1} to S_t in $VWKS$. All five lags are significant at the 1% level.

Panel B studies the 5-day moving average (MA) of $VWKS$ and its alternative measures using the following equation:

$$AQRET_{i,t} = \alpha + VWKS\_MA5 + AQRET\_MA5 + \epsilon.$$

In the first model, we report time series regression results using $VWKS\_MA5$ with regard to the risk adjusted mid quote returns. $VWKS\_MA5$ has a coefficient of 0.008, with a t-statistic of 33.47, statistically significant at the 1% level. The second model further controls for $AQRET\_MA5$, and the coefficient of $VWKS\_MA5$ becomes 0.007, with a t-statistic of 29.18, statistically significant at the 1% level. The third model uses risk adjusted raw returns ($ARET$) instead of risk adjusted mid quote returns. The average slope of $VWKS\_MA5$ is significant at the 1% level, with a coefficient of 0.008 and a t-statistic of 29.56. The fourth model uses mid quote returns ($QRET$), and the coefficient of

$VWKS\_MA5$ is 0.008, with a t-statistic of 25.58, statistically significant at the 1% level. In the fifth model, we tests the 5-day moving average (MA) of the log transformation of $VWKS$, $VWLNKS\_MA5$, which has a coefficient of 0.007, with a t-statistic of 28.18, statistically significant at the 1% level. In the sixth model, we tests the 5-day MA of the center of volume mass based on option *deltas*, $VWDELTA\_MA5$. The average slope of $VWDELTA\_MA5$ is significant at the 1% level, with a coefficient of -0.005 and a t-statistic of -6.09. The seventh model tests $VWKLS\_MA5$, the 5-day MA of $VWKLS$. $VWKS\_MA5$ has a coefficient of 0.005, with a t-statistic of 20.17, statistically significant at the 1% level.

In this subsection, we find that $VWKS$ is able to predict future returns (the risk adjusted mid quote returns and raw returns, as well as mid quote returns) in the time series regression. Even after controlling for the past returns in the regression, $VWKS$ and its 5-day MA are still significant at the 1% level. The predictability becomes weaker when we use $VWLNKS$, log transformation to normalize the variable; use $VWDELTA$, option *deltas* to measure moneyness instead of K/S; or use $VWKLS$, lagged stock price to eliminate the effect of return reversal. However, their 5-day MA are still significant at the 1% level. The strong return predictive ability of $VWKS$ in the time series regression is consistent with our conjecture that $VWKS$ captures informed trading in the options market.

5 Separating calls and puts

To better understand the nature of the return predictability, we analyze $VWKS$ using different types of options. We first compute volume weighted call options strike price over underlying stock price $VWKSCALL$, and volume weighted put options strike price over underlying stock price $VWKSPUT$. We then use $VWKSCALL\_MA5$ and $VWKSPUT\_MA5$, the 5-day moving averages of $VWKS_CALL$ and $VWKSPUT$, respectively in the Fama-Macbeth regressions, and report the results in Table A5.

[Table A5 about here]

The first model tests return predictive power of $VWKSCALL\_MA5$, which has a coefficient of 0.450 with a t-statistic of 3.16. In the second model, $VWKSCALL\_MA5$ has a coefficient of 0.269 with a t-statistic of 2.44 with the full set of control variables. The third model tests return predictive power of $VWKSPUT\_MA5$, which has a coefficient of 0.643 with a t-statistic of 4.26. In the fourth model, $VWKSPUT\_MA5$ has a coefficient of 0.437 with a t-statistic of 3.53 with the full set of control variables. The fifth model combines both $VWKSCALL\_MA5$ and $VWKSPUT\_MA5$, with coefficients of 0.265 and 0.451 respectively. They are significant at the 5% level and above. The result suggests that the center of options volume mass, using either call or put options, contains stock price information, and put contracts are more significant than call contracts statistically and economically.

6 Asymmetric pricing effects

In this subsection, we decompose $VWKS$ into a positive side and a negative side to test where the predictive power comes from. Positive $VWKS$ is defined as $VWKSP = max(VWKS, 0)$ and negative $VWKS$ is defined as $VWKSN = min(VWKS, 0)$. Similar to previous analysis, we test the moving averages of $VWKSP$ and $VWKSN$ in Table A6.

[Table A6 about here]

$VWKSP\_MA5$ is positive and significant at the 1% level in Table A6. In the first model, $VWKSP\_MA5$ alone has a coefficient of 0.359 with a t-statistic of 4.79. With the full set of control variables, the second model reports a coefficient of 0.174 for $VWKSP\_MA5$ with a t-statistic of 3.49. In the third model, $VWKSN\_MA5$ alone has an average slope coefficient of 0.346 with a t-statistic of 2.88. With the full set of control variables, the fourth model reports a coefficient of 0.335 for $VWKSN\_MA5$ with a t-statistic of 5.03. When combining $VWKSP\_MA5$ and $VWKSN\_MA5$ in model five, $VWKSP\_MA5$ has a coefficient of 0.14 (t-statistic = 2.19) and $VWKSN\_MA5$ has a coefficient of 0.199 (t-statistic = 1.95), significant at the 10% level. The result suggests that while both sides of $VWKS$ have positive impact on stock price, the positive side of $VWKS$ contains more information statistically while the negative side contains more information economically.

7 Non-linear pricing effects

We then test the predicting power from the tails of $VWKS$ distribution. Since $VWKS$ centers around zero, we create variable $VWKSSQ = sign(VWKS) * VWKS^2$, which is the signed $VWKS$ square. An absolute large value of $VWKSSQ$ implies it is at the tails of the distribution, where a positive sign indicates the right tail and a negative sign indicates the left tail. The empirical test is based on the following equation:

$$AQRET_{i,t} = \alpha + \beta_1 VWKSSQ\_MA5_{i,t-1} + \beta_2 VWKS\_MA5_{i,t-1} + \theta X\_MA5_{i,t-1} + \epsilon, \quad (2)$$

where $VWKSSQ\_MA5$ is the 5-day moving average of squared volume weighted strike price over underlying stock price. $VWKS\_MA5$ is the 5-day moving average of volume weighted strike price over underlying stock price.

[Table A7 about here]

We see positive and significant $VWKSSQ\_MA5$ at the 1% level in all four models in Table A7. $VWKSSQ\_MA5$ by itself (model one) has a coefficient as large as 0.571, with a t-statistic of 4.52. After controlling for other return predictors, we see a coefficient of 0.367 for $VWKSSQ\_MA5$ with a t-statistic of 2.95 in model two. In model three, after including $VWKS\_MA5$, we find $VWKSSQ\_MA5$ has a coefficient 0.364 and a t-statistic 2.91.

8 Center of options volume mass: *Levels* versus *Shocks*

We also test the predicting power from the shocks of $VWKS$. We first compute the past 20-day moving average of $VWKS$ as $VWKSMA20 = \sum_{j=1}^{20} VWKS_{t-j-5}/20$. Then we take $VWKS\_MA5$'s deviation from $VWKSMA20$ to obtain $VWKSS20 = VWKS\_MA5 - VWKSMA20$. The empirical test is based on the following equation:

$$AQRET_{i,t} = \alpha + \beta_1 VWKSS20_{i,t-1} + \beta_2 VWKSMA20_{i,t-1} + \theta X\_MA5_{i,t-1} + \epsilon. \qquad (3)$$

Table A8 reports Fama-MacBeth regression result of 20-day moving average and its shock, $VWKSMA20$ and $VWKSS20$.

[Table A8 about here]

We find that both $VWKSMA20$ and $VWKSS20$ can predict return positive and significant. The shock $VWKSS20$ has an average slope coefficient of 0.119 with a t-statistic of 2.36 in the first model by itself. With the full set of control variables, the coefficient becomes 0.055 with a t-statistic of 1.70 (model two). In the third model, the 20-day moving average $VWKSMA20$ has a coefficient of 0.283 with a t-statistic of 1.96 and after controlling for other return predictors from options market, the coefficient becomes 0.146 with a t-statistic of 4 in the fourth model. The fifth model combines both $VWKSMA20$ and $VWKSS20$ in full specification, where $VWKSS20$ has a coefficient of 0.107 (t-statistic = 2.88) and $VWKSMA20$ has a coefficient of 0.163 (t-statistic = 3.93). Comparing with the shocks, the 20-day moving average has a stronger economic significance.

Both 20-day moving average of $VWKS$ and its deviation positively predict future returns. The significance in the moving average from day $t-25$ to $t-6$ suggests that there is some delayed price response even beyond the first five days and the positive sign suggests that there is no reversal. However, a larger impact comes from the shock, due to arrival of new information. Therefore we see a much more significant $VWKSS20$ in the last model.

9 A case study: M&A's premiums

Mergers and acquisitions (M&A) provide an ideal setting in which to probe the implications of our main conjecture, since their announcements are unscheduled and contain hard information about the value of the offer for the target shares, which tend to entail large premiums relative to pre-offer prices. Therefore, there are ample incentives for informed agents to profit with by trading options. Consistent with this logic, options order imbalances lead stock returns ahead of M&A announcements (Cao, Chen, and Griffin (2005)) and implied volatility spreads predict M&A's announcement returns (Chan, Ge and Lin (2015)).[1]

Here, we examine whether lagged $VWKS$ explains variation in M&A premiums later disclosed at the time of the deal announcement. In particular, we estimate the following model by OLS:

$$MARET_{i,t} = \alpha + \beta VWKS\_MA5_{i,t-1} + \theta X\_MA5_{i,t-1} + \gamma Deal_i + \theta_n + \eta_T + \epsilon, \quad (4)$$

where $MARET_{i,t}$ is the offer premium relative to the last closing target stock price prior to announcement, $Deal_i$ is a vector of deal characteristics including the fraction of cash in the offer ($PctPay\_cash$), an indicator for hostile deals ($Att\_Hostile$), indicators for acquisitions by financial buyers ($AcqType\_FinPrvInst$) or by management ($AcqType\_EmplMgmt$) or by a listed acquirer ($AcqType\_PubCorp$). Industry affiliation is based on two-digit SIC codes. Table A9 reports the results of this analysis.

[Table A9 about here]

The first model presents regression results of a model where $VWKS\_MA5$ is the only explanatory variable. The average slope coefficient is 0.114 and the t-statistic is 4.97. Controlling for other return predictors from the options and stock markets, in the second model,

[1] In fact, the evidence in Lowry, Rossi, and Zhu (2018) indicates that informed trading ahead of M&As is more likely to occur in options than in equity markets.

$VWKS\_MA5$ has a coefficient of 0.091 and a t-statistic of 3.54. The third model further controls for the deal characteristics, and $VWKS\_MA5$ retains a coefficient of 0.093 with a t-statistic of 3.59. Out of all the other options market predictors, the implied skewness has a significant coefficient in model [2] but loses the predictive ability once deal characteristics are included. OS has a marginally significant coefficient in the full specification model but is unable to generate consistent predictability when the deal characteristics are not included. The results of this targeted analysis of M&A's announcements reinforces our conclusion that $VWKS$ reflects private information about the underlying stock. Other known return predictors from the options market appear to contain no such signal in the context of these well-defined and unambiguous corporate events. By contrast, both $VWKS\_MA5$ is an economically and statistically significant predictor of yet-to-be-announced offer premiums for the target shares, consistent with $VWKS$ containing information about upcoming deal announcements.

Table A1: Weekly univariate portfolio analysis

This table reports mean returns (in basis point) of weekly rebalanced single-sort decile portfolios for each options market predictor, mean return differentials between top and bottom decile portfolios, and corresponding long-short portfolio alpha's based on Fama-French (2015) and momentum factors. Stock returns are calculated using the midpoint of the bid and ask prices at market close adjusted for stock splits and dividends. Each portfolio is value-weighted using the component stock market capitalization. All variables are defined in Table 1. The t-statistics for mean return differentials and alpha's are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	VWKS	*PC*	*OS*	*DEV*	*SKEW*	*IVOL*	*DCIVOL*	*DPIVOL*	*VOLVOL*
Low	14.099	29.929	27.045	12.978	41.045	15.438	2.325	15.469	17.243
2	18.145	26.133	27.670	11.077	28.686	20.873	1.595	15.365	21.749
3	24.466	25.579	23.389	16.567	28.285	24.255	11.600	19.824	19.358
4	20.203	24.746	22.448	15.539	23.330	22.192	9.315	18.680	24.359
5	15.226	20.393	27.108	15.639	16.447	25.575	15.849	18.701	25.748
6	22.164	22.268	23.134	16.075	22.067	19.978	20.581	20.388	17.747
7	26.307	18.430	21.531	29.854	22.289	23.094	25.546	22.613	21.641
8	25.797	20.997	23.203	29.885	17.458	27.757	29.766	21.961	29.616
9	25.045	19.194	19.341	32.817	18.817	25.038	39.938	33.005	25.665
High	40.841	21.273	20.141	54.723	14.343	50.428	54.495	33.506	23.719
High-Low	26.743**	-8.656**	-6.904	41.744***	-26.702***	34.990**	52.170***	18.037**	6.475
	[2.50]	[-2.26]	[-1.26]	[6.97]	[-3.32]	[2.07]	[6.01]	[2.05]	[0.55]
FF5 alpha	38.510***	-3.519	-3.778	41.596***	-21.845***	12.917	51.799***	22.525***	-0.555
	[5.58]	[-1.07]	[-1.13]	[7.48]	[-4.20]	[1.64]	[7.22]	[3.28]	[-0.09]

Table A2: Double-sort portfolio analysis skipping one day

This table reports value-weighted average returns (in basis point) of daily rebalanced double-sorted quintile long-short portfolio alpha's based on Fama-French (2015) and momentum factors. We skip one day between the trading signal and forming the portfolio. Stock returns are calculated using the midpoint of the bid and ask prices at market close adjusted for stock splits and dividends. All variables are the same as defined in Table 1. To form portfolios, each day, we first sort all stocks into quintile portfolios based on a control variable - i.e., $QRET$, OS, PC, DEV, $SKEW$, $IVOL$, $DCIVOL$, $DPIVOL$, and $VOLVOL$. Then, within each quintile, we further sort stocks into quintiles based on $VWKS$. The t-statistics for return differentials and alpha's are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

VWKS	low	2	3	4	high
QRET	7.667***	4.348***	3.446**	3.689**	5.504**
	[3.52]	[2.64]	[2.25]	[2.36]	[2.81]
OS	0.825	3.660***	6.282***	9.872***	7.197***
	[1.12]	[3.11]	[3.81]	[4.88]	[3.28]
PC	6.414***	8.008***	7.145***	4.049**	3.137**
	[4.90]	[4.03]	[3.46]	[2.48]	[1.96]
DEV	8.458***	4.753***	6.418***	2.922	9.306***
	[4.31]	[2.70]	[3.79]	[1.61]	[4.35]
SKEW	8.435***	8.550***	6.827***	3.948**	8.726***
	[4.68]	[5.02]	[4.31]	[2.14]	[4.16]
IVOL	4.917***	2.909**	3.256*	8.781***	16.968***
	[5.48]	[2.17]	[1.87]	[4.16]	[6.43]
DCIVOL	6.327***	5.498***	4.849***	3.784**	10.617***
	[2.92]	[3.24]	[3.19]	[2.20]	[4.76]
DPIVOL	9.040***	4.321***	3.654**	6.638***	12.870***
	[4.32]	[2.59]	[2.32]	[3.77]	[5.60]
VOLVOL	5.124***	5.896***	2.090	7.687***	11.811***
	[4.66]	[4.42]	[1.27]	[3.66]	[4.91]

Table A3: Fama-MacBeth (1973) regressions with five daily lags

This table reports time-series averages of daily cross-sectional coefficients for the following model:

$$AQRET_{i,t} = \alpha + \sum_{l=1}^{5} \beta_l VWKS_{i,t-l} + \sum_{l=1}^{5} \theta_l X_{i,t-l} + \epsilon,$$

where $AQRET_{i,t}$ is the risk-adjusted mid quote stock return on day t for firm i, $VWKS_{i,t-i}$ is $VWKS$ measured on day $t-i$, and X is a vector containing daily values of PC, OS, DEV, $SKEW$, $IVOL$, $DCIVOL$, $DPIVOL$, $VOLVOL$, $AQRET$, $SPREAD$, $TURN$, and V. V is the square of the daily underlying stock return. All other variables are defined in Table A1. Columns (1)-(5) report coefficients estimated using the raw independent variables, while Column (6) reports standardized coefficients after transforming each independent variable to have a standard normal sample distribution. The t-statistics are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Intercept	-0.019***	-0.022***	-0.045***	-0.164***	-0.326***
	[-6.98]	[-8.21]	[-5.06]	[-9.80]	[-7.61]
LVWKS	0.216***	0.151***	0.141***	0.090***	0.083***
	[10.54]	[8.31]	[7.88]	[5.30]	[4.95]
L2VWKS		0.151***	0.131***	0.066***	0.056***
		[8.47]	[7.48]	[4.07]	[3.47]
L3VWKS		0.039**	0.040**	0.025	0.028
		[2.25]	[2.31]	[1.48]	[1.63]
L4VWKS		0.042**	0.045**	0.050***	0.046***
		[2.43]	[2.57]	[2.94]	[2.69]
L5VWKS		0.007	0.009	0.033*	0.035**
		[0.42]	[0.53]	[1.91]	[2.01]
LPC			-0.003***	-0.004***	-0.004***
			[-7.69]	[-10.13]	[-10.20]
L2PC			0.000	-0.001***	-0.001***
			[-0.88]	[-3.10]	[-3.44]
L3PC			0.000	-0.001**	-0.001**
			[-0.61]	[-1.98]	[-2.51]
L4PC			0.001	0.000	0.000
			[1.45]	[0.70]	[-0.14]
L5PC			0.000	0.000	0.000
			[0.51]	[1.00]	[0.42]
LOS			-0.002***	-0.002***	-0.002***
			[-4.09]	[-2.70]	[-2.75]
L2OS			0.000	-0.001*	-0.001*
			[-0.79]	[-1.69]	[-1.68]
L3OS			-0.001*	-0.002***	-0.002***
			[-1.94]	[-2.99]	[-2.73]
L4OS			0.000	-0.001	-0.001*
			[-0.04]	[-1.21]	[-1.87]

Table A3 (continued):

	(1)	(2)	(3)	(4)	(5)
L5OS			0.000	-0.001	-0.001
			[0.54]	[-1.18]	[-1.37]
LDEV			0.037	-0.007	0.028
			[0.19]	[-0.03]	[0.15]
L2DEV			0.26	0.269	0.328
			[1.19]	[1.22]	[1.47]
L3DEV			-0.350*	-0.3	-0.297
			[-1.67]	[-1.41]	[-1.35]
L4DEV			0.136	0.132	0.067
			[0.64]	[0.62]	[0.31]
L5DEV			0.197	0.172	0.137
			[1.16]	[1.02]	[0.78]
LSKEW			-0.281***	-0.235***	-0.251***
			[-7.13]	[-6.02]	[-6.35]
L2SKEW			-0.079*	-0.043	-0.028
			[-1.89]	[-1.03]	[-0.67]
L3SKEW			0.092**	0.052	0.046
			[2.27]	[1.28]	[1.11]
L4SKEW			-0.022	-0.038	-0.018
			[-0.54]	[-0.95]	[-0.44]
L5SKEW			0.054	0.022	0.026
			[1.50]	[0.62]	[0.72]
LIVOL			0.172	0.172	0.071
			[0.56]	[0.56]	[0.23]
L2IVOL			0.476	0.39	0.58
			[1.29]	[1.05]	[1.54]
L3IVOL			-0.813**	-0.885***	-0.899***
			[-2.40]	[-2.65]	[-2.65]
L4IVOL			-0.324	-0.246	-0.291
			[-1.02]	[-0.77]	[-0.90]
L5IVOL			0.482*	0.515**	0.580**
			[1.87]	[2.01]	[2.26]
LDCIVOL			0.279	0.202	0.284
			[1.07]	[0.77]	[1.08]
L2DCIVOL			-0.175	-0.244	-0.388
			[-0.70]	[-0.98]	[-1.53]
L3DCIVOL			0.592**	0.542**	0.437*
			[2.43]	[2.21]	[1.77]
L4DCIVOL			0.575***	0.516**	0.499**
			[2.74]	[2.45]	[2.30]
L5DCIVOL			0.110**	0.084*	0.062
			[2.40]	[1.82]	[1.33]
LDPIVOL			0.005	-0.145	-0.128
			[0.02]	[-0.59]	[-0.52]
L2DPIVOL			-0.07	-0.218	-0.125
			[-0.29]	[-0.91]	[-0.52]

Table A3 (continued):

	(1)	(2)	(3)	(4)	(5)
L3DPIVOL			-0.139	-0.117	-0.032
			[-0.56]	[-0.47]	[-0.13]
L4DPIVOL			0.214	0.215	0.253
			[0.96]	[0.97]	[1.13]
L5DPIVOL			0.101**	0.092*	0.075
			[2.05]	[1.88]	[1.53]
LVOLVOL			1.230**	0.782	0.622
			[2.09]	[1.33]	[1.07]
L2VOLVOL			-0.926	-0.498	-0.156
			[-0.95]	[-0.51]	[-0.16]
L3VOLVOL			-0.458	-0.11	-0.265
			[-0.51]	[-0.12]	[-0.30]
L4VOLVOL			-0.386	-0.748	-0.652
			[-0.45]	[-0.88]	[-0.77]
L5VOLVOL			0.537	0.498	0.31
			[1.12]	[1.04]	[0.64]
LAQRET				-0.794***	-1.467***
				[-5.91]	[-4.55]
L2AQRET				-1.176***	-0.534*
				[-9.94]	[-1.84]
L3AQRET				-0.618***	-0.525*
				[-5.96]	[-1.94]
L4AQRET				-0.577***	-0.292
				[-5.72]	[-1.14]
L5AQRET				-0.162	-0.287***
				[-1.64]	[-2.65]
LSPREAD				0.012	0.013
				[1.02]	[1.15]
L2SPREAD				-0.002	0.003
				[-0.14]	[0.27]
L3SPREAD				0.015	0.016
				[1.42]	[1.46]
L4SPREAD				0.011	0.011
				[1.01]	[1.04]
L5SPREAD				0.001	0
				[0.11]	[-0.02]
LTURN				0.076***	0.085***
				[18.96]	[21.15]
L2TURN				-0.017***	-0.014***
				[-5.19]	[-4.17]
L3TURN				-0.008**	-0.010***
				[-2.46]	[-2.72]
L4TURN				-0.001	-0.003
				[-0.28]	[-0.82]
L5TURN				-0.017***	-0.022***
				[-5.37]	[-6.64]

Table A3 (continued):

	(1)	(2)	(3)	(4)	(5)
$LRET^2$					-7.323***
					[-3.08]
$L2RET^2$					-7.039***
					[-3.57]
$L3RET^2$					0.34
					[0.18]
$L4RET^2$					-1.395
					[-0.71]
$L5RET^2$					4.342**
					[2.29]
LBM					0.566***
					[3.06]
L2BM					-1.188***
					[-4.79]
L3BM					0.276
					[1.18]
L4BM					0.12
					[0.50]
L5BM					0.285
					[1.60]
LIdioVol					-0.15
					[-0.39]
L2IdioVol					0.609
					[1.03]
L3IdioVol					-0.684
					[-1.16]
L4IdioVol					0.939*
					[1.68]
L5IdioVol					-0.845**
					[-2.14]
LSIZE					1.613***
					[5.27]
L2SIZE					-2.433***
					[-6.46]
L3SIZE					0.483
					[1.42]
L4SIZE					-0.1
					[-0.31]
L5SIZE					0.443*
					[1.85]

Table A3 (continued):

	(1)	(2)	(3)	(4)	(5)
LOIB					-0.011*
					[-1.70]
L2OIB					0.008
					[1.19]
L3OIB					0.006
					[0.86]
L4OIB					-0.007
					[-1.05]
L5OIB					-0.007
					[-0.59]
adj. R^2	0.002	0.005	0.035	0.056	0.077
Obs per day	1100	1100	1100	1100	1100

Table A4: Time-series regression analysis

This table reports mean coefficients of stock-level time-series regressions of daily risk adjusted mid quote returns on $VWKS$. Panel A reports mean time-series estimates for various versions of the following model:

$$AQRET_{i,t} = \alpha + \sum_{l=1}^{5} \beta_l VWKS_{i,t-l} + \sum_{l=1}^{5} \theta_l AQRET_{i,t-l} + \epsilon,$$

where $AQRET_{i,t}$ is the risk adjusted mid quote returns on day t. The model in Column (1) includes only one lag of $VWKS$. The model in Column (2) includes five lags of $VWKS$. Column (5) adds five lags of $AQRET$. Column (4) uses risk adjusted raw returns instead of risk adjusted mid quote returns. Column (5) uses mid quote returns instead of risk adjusted mid quote returns. Column (6) replaces $VWKS$ with its log-transformation, $VWLNKS$. Column (7) replaces $VWKS$ with its equivalent based on option *delta*, $VWDELTA$. Column (8) replaces $VWKS$ with $VWLKS$, where the KS ratio is based on S_{t-1} instead of S_t. Panel B repeats the analysis using 5-day moving averages of the explanatory variables instead of the individual daily lags. The t-statistics are reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

Table A4 (continued):

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y	*AQRET*	*AQRET*	*AQRET*	*ARET*	*QRET*	*AQRET*	*AQRET*	*AQRET*
X	*VWKS*	*VWKS*	*VWKS*	*VWKS*	*VWKS*	*VWLNKS*	*VWDELTA*	*VWKLS*
LVWKS1	0.004***	0.002***	0.002***	0.002***	0.002***	0.002***	0.000	0.002***
	[24.57]	[14.37]	[10.95]	[13.13]	[11.01]	[11.34]	[-0.75]	[9.25]
LVWKS2		0.003***	0.002***	0.002***	0.002***	0.002***	-0.002***	0.002***
		[15.53]	[11.70]	[11.38]	[10.82]	[12.04]	[-3.32]	[9.89]
LVWKS3		0.001***	0.001***	0.001***	0.001***	0.001***	-0.001***	0.001***
		[8.12]	[7.75]	[7.79]	[5.01]	[7.98]	[-2.79]	[5.22]
LVWKS4		0.001***	0.001***	0.001***	0.001***	0.001***	-0.001***	0.001***
		[8.29]	[8.97]	[8.87]	[7.03]	[8.81]	[-2.61]	[7.47]
LVWKS5		0.001***	0.001***	0.001***	0.001***	0.001***	-0.001	0.001***
		[6.53]	[8.34]	[8.03]	[6.10]	[7.97]	[-1.51]	[5.97]
LAQRET1			-0.007***	-0.015***	0.005***	0.002***	-0.007***	-0.006***
			[-5.08]	[-11.11]	[4.72]	[11.34]	[-5.03]	[-4.00]
LAQRET2			-0.018***	-0.018***	-0.019***	0.002***	-0.018***	-0.016***
			[-22.24]	[-22.21]	[-25.63]	[12.04]	[-23.04]	[-18.73]
LAQRET3			-0.008***	-0.008***	-0.001**	0.001***	-0.009***	-0.007***
			[-11.22]	[-11.25]	[-2.31]	[7.98]	[-12.79]	[-8.61]
LAQRET4			-0.006***	-0.006***	-0.003***	0.001***	-0.008***	-0.006***
			[-8.98]	[-8.96]	[-5.42]	[8.81]	[-10.96]	[-7.98]
LAQRET5			-0.004***	-0.004***	-0.010***	0.001***	-0.006***	-0.003***
			[-5.88]	[-5.76]	[-16.07]	[7.97]	[-9.00]	[-4.33]
Intercept	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	-0.000***	0.003***	-0.000***
	[-24.88]	[-33.47]	[-37.74]	[-38.68]	[77.18]	[-45.91]	[6.12]	[-56.16]
adj. R^2	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000
Obs	6778197	6761765	6745857	6745857	6745857	6745857	6757576	6710091

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y	*AQRET*	*AQRET*	*ARET*	*QRET*	*AQRET*	*AQRET*	*AQRET*
X	*VWKS*	*VWKS*	*VWKS*	*VWKS*	*VWLNKS*	*VWDELTA*	*VWKLS*
VWKS_MA5	0.008***	0.007***	0.008***	0.008***	0.007***	-0.005***	0.005***
	[33.47]	[29.18]	[29.56]	[25.58]	[28.18]	[-6.09]	[20.17]
AQRET_MA5		-0.043***	-0.051***	-0.030***	-0.043***	-0.048***	-0.038***
		[-20.36]	[-23.46]	[-16.11]	[-20.56]	[-22.62]	[-14.21]
Intercept	-0.000***	-0.000***	-0.000***	0.001***	-0.000***	0.003***	-0.000***
	[-33.47]	[-29.39]	[-29.81]	[84.18]	[-28.63]	[6.09]	[-19.93]
adj. R^2	0.000	0.000	0.000	0.001	0.000	0.000	0.000
Obs	6782239	6782239	6782239	6782239	6782239	6757576	6789851

Table A5: Center of trading volume mass in call and put options

This table reports Fama-MacBeth (1973) estimates of the following model:

$$AQRET_{i,t} = \alpha + \beta_1 VWKSCALL\_MA5_{i,t-1} + \beta_2 VWKSPUT\_MA5_{i,t-1} + \theta X\_MA5_{i,t-1} + \epsilon,$$

where $AQRET_{i,t}$ is the risk adjusted mid quote returns on day t. $VWKSCALL\_MA5$ is the 5-day moving average (MA) of volume weighted call options strike price over underlying stock price minus one. $VWKSPUT\_MA5$ is the 5-day MA of volume weighted put options strike price over underlying stock price minus one. The X_MA5 is the full set of control variables measured on day $t-1$. Columns (1)-(5) report coefficients estimated using the raw independent variables. The t-statistics are adjusted following Newey-West (1987) and reported in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Intercept	-0.002	-0.295***	0.000	-0.295***	-0.295***
	[-0.13]	[-3.69]	[0.03]	[-3.69]	[-3.69]
VWKSCALL_MA5	0.450***	0.269**			0.265**
	[3.16]	[2.44]			[2.38]
VWKSPUT_MA5			0.643***	0.437***	0.451***
			[4.26]	[3.53]	[3.60]
PC_MA5		-0.003***		-0.003***	-0.003***
		[-3.11]		[-3.07]	[-3.07]
OS_MA5		-0.009***		-0.009***	-0.009***
		[-4.01]		[-3.94]	[-3.97]
DEV_MA5		0.093		0.096	0.096
		[0.81]		[0.85]	[0.84]
SKEW_MA5		-0.259***		-0.257***	-0.257***
		[-3.91]		[-3.88]	[-3.88]
IVOL_MA5		0.127**		0.128**	0.126**
		[2.36]		[2.38]	[2.35]
DCIVOL_MA5		0.365***		0.364***	0.364***
		[3.31]		[3.31]	[3.31]
DPIVOL_MA5		-0.128		-0.127	-0.126
		[-1.20]		[-1.19]	[-1.18]
VOLVOL_MA5		-0.092		-0.093	-0.092
		[-0.69]		[-0.70]	[-0.69]
AQRET_MA5		0.208		0.21	0.216
		[0.90]		[0.91]	[0.94]
SPREAD_MA5		0.075**		0.074**	0.074**
		[2.14]		[2.11]	[2.12]
TURN_MA5		0.012*		0.012*	0.013*
		[1.83]		[1.83]	[1.84]
V_MA5		-2.55		-2.569	-2.569
		[-1.21]		[-1.22]	[-1.22]
BM_MA5		0.051***		0.050***	0.050***
		[4.02]		[4.01]	[4.01]
IdioVol_MA5		-0.029		-0.026	-0.027
		[-0.35]		[-0.32]	[-0.34]
SIZE_MA5		0.008**		0.008**	0.008**
		[2.53]		[2.57]	[2.57]
OIB_MA5		-0.044**		-0.044**	-0.044**
		[-2.21]		[-2.18]	[-2.18]
adj. R^2	0.001	0.056	0.000	0.056	0.056
Obs per day	1200	1200	1200	1200	1200

Table A6: Asymmetric price impact from center of options volume mass

This table reports Fama-MacBeth (1973) estimates of the following model:

$$AQRET_{i,t} = \alpha + \beta_1 VWKSP\_MA5_{i,t-1} + \beta_2 VWKSN\_MA5_{i,t-1} + \theta X\_MA5_{i,t-1} + \epsilon,$$

where $AQRET_{i,t}$ is the risk adjusted mid quote returns on day t. $VWKSP\_MA5$ is the 5-day moving average (MA) of volume weighted strike price over underlying stock price minus one if strike price is larger than stock price, zero otherwise. $VWKSN\_MA5$ is the 5-day MA of volume weighted strike price over underlying stock price minus one if strike price is smaller than stock price, zero otherwise. The X_MA5 is a set of control variables on day $t-1$ defined as in Table 6. In the last column, we standardize $VWKS$ by firm, take the 5-day MA to obtain $VWKS\_MA5$, then assign the positive $VWKS\_MA5$ to be $VWKSP\_MA5$ and negative $VWKS\_MA5$ to be $VWKSN\_MA5$. Standard errors are calculated with the Newey-West adjustment. Associated t-statistics are reported in parentheses ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Intercept	-0.017	-0.331***	0.006	-0.291***	-0.308***
	[-1.30]	[-4.10]	[0.45]	[-3.64]	[-3.83]
VWKSP_MA5	0.359***	0.174***			0.140**
	[4.79]	[3.49]			[2.19]
VWKSN_MA5			0.346***	0.335***	0.199*
			[2.88]	[5.03]	[1.95]
PC_MA5		-0.003***		-0.003***	-0.004**
		[-3.33]		[-2.59]	[-2.58]
OS_MA5		-0.009***		-0.009***	-0.009***
		[-4.27]		[-4.29]	[-4.62]
DEV_MA5		0.123		0.103	0.114
		[1.09]		[0.92]	[1.01]
SKEW_MA5		-0.256***		-0.263***	-0.254***
		[-4.16]		[-4.31]	[-4.16]
IVOL_MA5		0.129**		0.145***	0.130**
		[2.45]		[2.74]	[2.47]
DCIVOL_MA5		0.347***		0.382***	0.373***
		[3.06]		[3.44]	[3.37]
DPIVOL_MA5		-0.132		-0.146	-0.136
		[-1.21]		[-1.35]	[-1.24]
VOLVOL_MA5		-0.055		-0.044	-0.043
		[-0.40]		[-0.32]	[-0.31]
AQRET_MA5		0.482*		0.460*	0.499*
		[1.89]		[1.81]	[1.96]
SPREAD_MA5		0.081**		0.088**	0.084**
		[2.29]		[2.47]	[2.38]
TURN_MA5		0.016**		0.014**	0.015**
		[2.36]		[1.99]	[2.18]
V_MA5		-7.941**		-7.660**	-7.844**
		[-2.27]		[-2.19]	[-2.25]
BM_MA5		0.050***		0.050***	0.050***
		[3.99]		[3.98]	[3.95]
IdioVol_MA5		-0.028		-0.028	-0.029
		[-0.34]		[-0.34]	[-0.35]
SIZE_MA5		0.009***		0.007**	0.008**
		[2.76]		[2.25]	[2.43]
OIB_MA5		-0.047**		-0.047**	-0.048**
		[-2.22]		[-2.23]	[-2.26]
adj. R^2	0.005	0.055	0.002	0.055	0.056
Obs per day	1200	1200	1200	1200	1200

Table A7: Nonlinear pricing impact from center of options volume mass

This table reports Fama-MacBeth (1973) estimates of the following model:

$$AQRET_{i,t} = \alpha + \beta_1 VWKSSQ\_MA5_{i,t-1} + \beta_2 VWKS\_MA5_{i,t-1} + \theta X\_MA5_{i,t-1} + \epsilon,$$

where $AQRET_{i,t}$ is the risk adjusted mid quote returns on day t. $VWKSSQ\_MA5$ is the 5-day moving average (MA) of squared volume weighted strike price over underlying stock price minus one. $VWKS\_MA5$ is the 5-day MA of volume weighted strike price over underlying stock price minus one. The X_MA5 is a set of control variables on day $t-1$ defined as in Table 6. In the last column, we standardize $VWKS$ and $VWKSSQ$ by firm, then take the 5-day MA to obtain $VWKS\_MA5$ and $VWKSSQ\_MA5$ respectively. Standard errors are calculated with the Newey-West adjustment. Associated t-statistics are reported in parentheses ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Intercept	-0.016***	-0.132***	-0.292***
	[-3.94]	[-3.37]	[-3.65]
KSSQ_MA5	0.571***	0.367***	0.364***
	[4.52]	[2.95]	[2.91]
VWKS_MA5		0.086	0.069
		[1.32]	[1.08]
PC_MA5		-0.002	-0.003**
		[-1.57]	[-2.30]
OS_MA5		-0.004***	-0.004***
		[-2.59]	[-2.73]
DEV_MA5		-0.017	-0.037
		[-0.15]	[-0.33]
SKEW_MA5		-0.300***	-0.320***
		[-5.05]	[-5.34]
IVOL_MA5		0.097**	0.127**
		[2.12]	[2.48]
DCIVOL_MA5		1.109***	1.168***
		[3.83]	[4.04]
DPIVOL_MA5		-0.509*	-0.569*
		[-1.73]	[-1.93]
VOLVOL_MA5		-0.09	-0.127
		[-0.86]	[-1.20]
AQRET_MA5		0.427	0.444
		[0.79]	[0.83]
SPREAD_MA5		0.130***	0.155***
		[2.77]	[3.36]
TURN_MA5		0.006	0.006
		[0.85]	[0.81]
V_MA5		0.107	0.197
		[0.04]	[0.07]
BM_MA5			0.048***
			[4.19]
IdioVol_MA5			-0.038
			[-0.50]
SIZE_MA5			0.009***
			[2.76]
OIB_MA5			-0.051*
			[-1.93]
adj. R^2	0.001	0.033	0.037
Obs per day	1200	1200	1200

Table A8: Long-term moving average of and shock to center of options volume mass
This table reports Fama-MacBeth (1973) estimates of the following model:

$$AQRET_{i,t} = \alpha + \beta_1 VWKSS20_{i,t-1} + \beta_2 VWKSMA20_{i,t-1} + \theta X\_MA5_{i,t-1} + \epsilon,$$

where $AQRET_{i,t}$ is the risk adjusted mid quote returns on day t. $VWKSMA20$ is the past 20-day moving average (MA) of volume weighted strike price over underlying stock price minus one from day $t-25$ to day $t-6$. $VWKSS20$ is the difference between 5-day MA of $VWKS$ and $VWKSMA20$. The X_MA5 is a set of control variables on day $t-1$ defined as in Table 6. In the last column, all explanatory variables are standardized so as to have the same mean, 0, and standard deviation equal, 1. Standard errors are adjusted following Newey-West (1987). t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Intercept	-0.003	-0.296***	-0.007	-0.291***	-0.300***
	[-0.20]	[-3.70]	[-0.54]	[-3.64]	[-3.75]
VWKSS20	0.119**	0.055*			0.107***
	[2.36]	[1.70]			[2.88]
VWKSMA20			0.283*	0.146***	0.163***
			[1.96]	[4.00]	[3.93]
PC_MA5		-0.003***		-0.003***	-0.003***
		[-2.97]		[-2.81]	[-2.76]
OS_MA5		-0.009***		-0.009***	-0.010***
		[-4.04]		[-4.08]	[-4.16]
DEV_MA5		0.098		0.09	0.128
		[0.86]		[0.79]	[1.15]
SKEW_MA5		-0.261***		-0.241***	-0.252***
		[-3.92]		[-3.64]	[-4.11]
IVOL_MA5		0.130**		0.109**	0.117**
		[2.42]		[2.03]	[2.26]
DCIVOL_MA5		0.364***		0.373***	0.371***
		[3.31]		[3.40]	[3.39]
DPIVOL_MA5		-0.131		-0.128	-0.126
		[-1.23]		[-1.20]	[-1.18]
VOLVOL_MA5		-0.094		-0.083	-0.079
		[-0.70]		[-0.62]	[-0.59]
AQRET_MA5		0.214		0.217	0.25
		[0.93]		[0.94]	[1.08]
SPREAD_MA5		0.073**		0.072**	0.072**
		[2.09]		[2.07]	[2.05]
TURN_MA5		0.013*		0.013*	0.013*
		[1.83]		[1.87]	[1.90]
V_MA5		-2.562		-2.532	-2.562
		[-1.22]		[-1.20]	[-1.22]
BM_MA5		0.051***		0.049***	0.048***
		[4.01]		[3.91]	[3.88]
IdioVol_MA5		-0.028		-0.029	-0.028
		[-0.34]		[-0.36]	[-0.35]
SIZE_MA5		0.008**		0.008**	0.008**
		[2.54]		[2.54]	[2.53]
OIB_MA5		-0.045**		-0.042**	-0.042**
		[-2.22]		[-2.07]	[-2.10]
adj. R^2	0.004	0.057	0.006	0.057	0.058
Obs per day	1200	1200	1200	1200	1200

Table A9: Center of options volume mass and M&A's offer premiums

This table reports ordinary least squares estimates of the following model:

$$MARET_{i,t} = \alpha + \beta VWKS\_MA5_{i,t-1} + \theta X\_MA5_{i,t-1} + \gamma Deal_i + \theta + \eta + \epsilon,$$

where θ and η are industry and calendar-year fixed effects, respectively; $MARET_{i,t}$ is the M&A's offer premium over the target closing stock price one day prior to announcement; $Deal$ is a set of deal characteristics including the percentage of cash paid, $PctPay\_cash$, a hostile deal dummy, $Att\_Hostile$, a dummy for financial acquirers, $AcqType\_FinPrvInst$, a dummy for management and employees acquirers, $AcqType\_EmplMgmt$, and a dummy for public firm acquirers, $AcqType\_PubCorp$. Industry affiliation is based two-digit SIC codes. Robust t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% probability levels, respectively.

	(1)	(2)	(3)
Intercept	0.262***	0.170**	0.094
	[31.27]	[2.23]	[1.15]
VWKS_MA5	0.114***	0.091***	0.093***
	[4.97]	[3.54]	[3.59]
PC_MA5		0.000	0.000
		[0.12]	[0.26]
OS_MA5		-0.001	-0.002*
		[-1.24]	[-1.79]
DEV_MA5		-0.061	-0.045
		[-1.51]	[-1.09]
SKEW_MA5		-0.055**	-0.041
		[-2.02]	[-1.49]
IVOL_MA5		0.008	0.011
		[0.75]	[0.92]
DCIVOL_MA5		0.431	0.397
		[1.00]	[0.92]
DPIVOL_MA5		-0.139	-0.25
		[-0.32]	[-0.56]
VOLVOL_MA5		-0.32	-0.313
		[-1.29]	[-1.24]
AQRET_MA5		-0.309***	-0.361***
		[-2.60]	[-2.97]
SPREAD_MA5		-0.002	-0.002
		[-0.74]	[-0.68]
TURN_MA5		0.004	0.004
		[1.37]	[1.41]
PctPay_cash			0.000
			[0.75]
Att_Hostile			-0.007
			[-0.12]
AcqType_FinPrvInst			-0.031
			[-1.02]
AcqType_EmplMgmt			0.054
			[0.81]
AcqType_PubCorp			0.093***
			[3.68]
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
R^2	0.273	0.284	0.300
Obs	1516	1516	1516