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Chapter 1 studies volatility tail risk and its asset pricing implications. Motivated by dynamic models featuring jumps in stochastic volatility, I examine the economic behaviors and the pricing of volatility tail risk in the cross-section of asset prices, including stocks and options. Using intraday option dataset, I construct a novel non-parametric volatility tail risk measure from high-frequency implied volatility data and find a strong negative effect associated with volatility tail risk: stocks with high volatility tail risk robustly underperform stocks with low volatility tail risk. In particular, the negative price of volatility tail risk is driven systematic component through decomposition. The volatility tail risk measure is strongly related to jump components in the volatility process identified using non-parametric approach, and is the best predictor of future average jump intensity and jump size. Furthermore, the volatility tail risk measure plays an important role in predicting future economic variables: it positively and robustly predicts future equity return jump risk, volatility risk premium, idiosyncratic volatility, stock return high-order moments, illiquidity measure and volatility skew. Finally, it predicts future risk-neutral option straddle return as well as volatility risk premium, measured as the difference between implied volatility and realized volatility.

Chapter 2 (joint with Dimitry Muravyev) studies the seasonality of option returns. We show that average returns for S&P 500 index options are negative and large: -0.7% per day. Strikingly, when we decompose these delta-hedged option returns into intraday (open-to-close) and overnight (close-to-open) components, we find that average overnight returns are -1%, while intraday returns are actually positive, 0.3% per day. A similar return pattern holds for all maturity and moneyness categories, and equity options. Rational theories struggle to explain positive intraday returns. However, our results are consistent with option prices failing to account for the well-known fact that stock volatility is substantially higher intraday than overnight. These results help us better understand the price formation in the options market.

Chapter 3 (joint with Dimitry Muravyev) studies option informed trades and the connections with stock return predictability. We show that option order imbalances predict the cross-section of equity returns. We show that a large part of this predictability can be attributed as one-day announcement effect. Predictability of option order imbalances declines as forecasting horizon prolongs. In particular, we show

that, the predictability of long-horizon predictability depends on the privacy of information. Public disclosure of option trades information has a crucial and negative impact on the predictability of option order imbalances. Furthermore, using identification algorithms, we can imprecisely distinguish between investor’s trades and option market maker’s trades and find that, the order imbalances from non-option market makers contain almost all information relevant for predicting future stock returns. Our results are consistent with theories implying that option trading volume reflects the actions of informed traders, and the action of disclosing this information can facilitate asset price movements.

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Finally, I thank my fellow graduate students for their helpful comments and friendship. I dedicate this thesis to my parents and friends, without whose love and support completing this thesis would not have been possible.

Volatility Tail Risk and Asset Prices

Xuechuan (Charles) Ni*†

ABSTRACT

Motivated by dynamic models featuring jumps in stochastic volatility, I examine the economic behaviors and the pricing of volatility tail risk in the cross-section of asset prices, including stocks and options. Using intraday option dataset, I construct a novel non-parametric volatility tail risk measure from high-frequency implied volatility data and find a strong negative effect associated with volatility tail risk: stocks with high volatility tail risk robustly underperform stocks with low volatility tail risk. In particular, the negative price of volatility tail risk is driven systematic component through decomposition. The volatility tail risk measure is strongly related to jump components in the volatility process identified using non-parametric approach, and is the best predictor of future average jump intensity and jump size. Furthermore, the volatility tail risk measure plays an important role in predicting future economic variables: it positively and robustly predicts future equity return jump risk, volatility risk premium, idiosyncratic volatility, stock return high-order moments, illiquidity measure and volatility skew. Finally, it predicts future risk-neutral option straddle return as well as volatility risk premium, measured as the difference between implied volatility and realized volatility.

JEL classification: G11, G12, G17.

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Recent finance literature shows that jumps in price and volatility play a very important role in explaining equity risk premium as well as the wedge between stock price and option price. For example, Bollerslev and Todorov (2011) uses intraday index future data to demonstrate that the compensation for tail events accounts for a large fraction of the equity risk premium and variance risk premium. Pan (2002) reveals that the jump component in the stochastic volatility process is crucial in explaining the joint dynamics of both S&P 500 index and short-term index option prices. While numerous literature examine how tail risks of return and volatility explain the dynamics of aggregate stock market behavior, the questions of how to measure volatility tail risk without structural restrictions and how volatility tail risk affects the cross-section of expected stock returns and economic conditions have received less attention.

First and foremost, one of the realistic questions is: do stock volatility jumps? This is quite natural to ask before we explore further. In academic research, we are always trying to build models such that they can accommodate asset pricing phenomenon from different markets. Studies on volatility jumps in complex structural models are firstly introduced by Bates (2000) and Pan (2002). Their estimates are obtained from options data and joint returns/options data, respectively. They conclude that jumps in stock returns do not adequately describe the systematic variations in option prices. Results in both papers point toward models that include jumps in volatility process. In response to these findings, Eraker, Johannes, and Polson (2003) uses returns data only to investigate the performance of models with jumps in volatility as well as in prices (henceforth EJP). The results show that EJP provides a significantly better fit to the returns data. Eraker (2004) has provided answers from a model-fitting perspective using joint returns/options data. Eraker (2004) concludes that models with volatility jumps indeed fit options and stock returns data simultaneously in a better way.

The volatility expectation, or IV, captures the uncertainty in investors' assessments of these risks. As argued by Baltussen, Bekkum, and Grient (2014), the main advantage of using option market information is that option prices are forward-looking by nature, making them an appealing basis to measure investors' uncertainty about risk *ex ante*. Options are written on the stock itself, traded by a large number of agents, and observed on a daily frequency. Thus, unlike for example earnings estimated by analysts or survey forecasts by other investment professionals, expectations are extracted from actual financial market transactions. Being derived directly from market prices also circumvents self-selection problems and optimism bias in analyst forecasts (e.g., McNichols and O'Brien (1997)), and prevents distortions by incentive-related effects.

Furthermore, IV innovations are also related to innovations in expected stock volatility as well as stock returns. Dennis, Mayhew, and Stivers (2006) explores the relation between daily stock returns and daily innovations in option-derived IVs. Their results indicate that the relation between stock returns and innovations in systematic volatility (idiosyncratic volatility) is substantially negative (near zero). They also provide evidence that innovations in implied volatility are good proxies for innovations in expected stock volatility. Besides, IV is closely related to many option-related characteristics that prove to strongly predict future stock returns in the finance literature. For example, Conrad, Dittmar, and Ghysels (2013) shows that ex ante moments predict expected stock returns. They show that even after controlling for differences in co-moments, ex ante skewness still matters. Xing, Zhang, and Zhao (2010) shows that volatility smirk negatively predicts future stock returns, which persists for at least 6 months. Bali and Hovakimian (2009) finds that volatility spread (RV-IV) can be viewed as a good proxy for volatility risk and thus, predicts the cross-sectional variation in expected stock returns.

Motivated by dynamic models featuring jumps in volatility[1], the objective of this paper is to construct a novel non-parametric volatility tail risk measure, and examine the impact of volatility tail risk on future economic quantities as well as its pricing implications in the cross-section (and time-series) of stock returns. This paper also explores the economic linkages between volatility tail risk and other economic state variables. In papers such as Eraker et al. (2003), however, jumps are identified under specific structural models, and they don't focus on exploring the pricing in the cross-section. Building on the idea proposed by Bollerslev and Todorov (2011), I construct my daily tail risk measure of volatility using intraday implied volatility estimated from at-the-money options with time-to-maturity closest to 30 days. Implied volatility (IV) is by far one of the best predictors of future stock returns in the cross-section, and captures investors' conditional expectations of future realized volatility. Consequently, the tail risk of IV can be treated as a reliable proxy for how market participants perceive "volatility tail risk". Then, I aggregate the daily volatility tail risk measure to obtain monthly volatility tail risk measure (VTR). There are two arguments for doing at monthly frequency which I perceive as nontrivial: first, aggregating to monthly frequency can smooth the

[1] For example, Pan (2002), Eraker et al. (2003), Eraker (2004), and Broadie, Chernov, and Johannes (2007).

micro-structure noise and frictions from intraday data. This is particular important because 1-minute option quote data is used. Second, IV is generally persistent for a given stock, which means that the volatility tail risk measure will be relatively persistent with long-term predictability. This differs from information-driven stock return predictability (e.g., Johnson and So (2012), Hu (2014)).

There are multiple advantages of using my proposed non-parametric measures: (1) first of all, the advantage of using non-parametric measure, in contrast to parametric measure (i.e. complex structural models), is that non-parametric approach is immune to model misspecifications. Frankly speaking, unlike experimental science, it is hard to testify the validity of a model. Furthermore, structural models with stochastic volatility, as well as jumps in stock return and volatility (namely, multiple hidden factors), make the accurate estimation of parameters a tough task even with MH algorithm and Gibbs sampling. (2) The primary reason for using high-frequency quadratic variations is motivated by Bollerslev and Todorov (2011). In their paper, they discuss that if we assume that stock return process driven by a diffusion component and a jump component, then the tail variation of intraday quadratic variation can be viewed as a reliable measure of realized jumps in intraday stock returns. Furthermore, the assumption that instantaneous volatility follows geometric Brownian motion is also widely used in finance literature, for example, Huang and Shaliastovich (2014). Therefore, given the mathematical inductions in Bollerslev and Todorov (2011) paper, I argue that the VTR measure in my paper can reasonably capture tail variations in intraday IV change. (3) Compared to the measure proposed by Kelly and Jiang (2014) (hence, KJ), they propose a new measure of time-varying tail risk that is directly estimated using from the cross-section of stock returns. Their estimator relies critically on the assumption that they assume the tail distributions of all stock returns have similar power-law distribution. This critical assumption, albeit it seems to work well in the paper, is hard to validate. The mathematical formulae between VTR and KJ is not directly comparable, therefore, we will compare them empirically in the paper.

On introducing a novel volatility tail risk measure, I validate this measure from multiple aspects. First, I analyze the connection between volatility tail risk and equity return jump measure, $ERJM$. I show that volatility jumps and stock return jumps are empirically uncorrelated for SPY (reliable proxy for SPX) time series: the correlation is merely *0.01* with no statistical significance. I also test the market return predictability using VTR, $ERJM$, VRP (short for volatility risk premium) and dividend-price ratio (or D/P). I show that VTR negatively predicts future stock return even after controlling for other predictors.

Second, I compare the relation between VTR and other crucial firm characteristics. In particular, to make economic magnitudes comparable, I standardize each variable to zero mean and unit variance. I first conduct a VTR explanatory analysis by regressing VTR on other firm controls (contemporaneously). The results show that only Size, Amihud (stock liquidity measure), and OptSpread (option liquidity measure) can explain over 10% cross-sectional VTR variations. Together with other controls, only 30% contemporaneous cross-sectional variations of VTR can be explained. A large fraction of information contained in VTR remain unexplained. Then I conduct a large panel VAR analysis by predicting future economic variables, including VTR, $ERJM$, VRP: first of all, the volatility tail risk is persistent in the cross-section with an autocorrelation of 0.44 after controlling for other factors. It is also the most effective predictor of itself among others. In addition, we show that the proposed volatility tail risk measure, VTR, is an effective predictor of future equity return jump measure and volatility risk premium. It also positively predicts future idiosyncratic volatility and illiquidity measures, i.e. Amihud and OptSpread.

Third, to validate that VTR indeed measures jump components in IV process, I use a novel non-parametric approach proposed by Lee and Mykland (2007) to identify jumps in the IV process. Built on the identified jumps from IV process, I develop three extended IV jump measures: IVJI, IVJS and IVSJS. IVJI stands for IV jump intensity. IVJS represents IV jump size and IVSJS stands for IV scaled jump size. I show that VTR is robustly related to all three IV jump measures, particularly for IVSJS. Furthermore, after controlling for other crucial firm characteristics, we show that VTR is one of the most effective predictor of future IV jump measures. The average coefficient of predicting IVJI/IVJS/IVSJS is 0.207, which is the largest in economic magnitude among all other economic variables. This serves as very strong evidence that my VTR captures future IV jumps in an effective way.

How volatility tail risk is priced in the stock market? We find strong evidence that stocks with high volatility tail risk (high VTR) robustly underperform stocks with low volatility tail risk, that is, volatility tail risk bears a negative effect in the cross-section. After sorting stocks into quintile portfolios based on VTR, the long-short strategy that buys stocks with the highest VTR and sells stocks with the lowest VTR generates an average monthly return of -43.6 basis points (-5.23% per annum) with a t-statistic of -2.41. The corresponding Carhart (1997) four-factor risk-adjusted alpha for the long-short VTR portfolio is -42.2 basis points per month (-5.1% per annum) with a t-statistic of -2.67. The magnitude of the return difference is both economically and statistically significant. The cross-sectional results, at first glance, are not in line with existing risk compensation models with rational expectations. I also show that the negative volatility tail risk effect is persistent up to about 4 months after portfolio formation. This evidence is opposed to the view that the negative volatility tail risk effect is a mispricing phenomenon. Empirically, it is attractive to think of the negative volatility risk effect as another piece of anomaly analogous to the idiosyncratic volatility puzzle documented by Ang, Hodrick, Xing, and Zhang (2006) and Ang, Hodrick, Xing, and Zhang (2009).

Next, I further confirm that the negative relation between the volatility tail risk measure, VTR, and future stock returns in the cross-section using Fama and MacBeth (1973) regressions. In Fama-MacBeth regressions, after controlling for a set of well-documented firm and option characteristics, a one-standard deviation increase in VTR is associated with a 1.2%-standard deviation drop in monthly return.The volatility tail risk effect is robust to a battery of control variables, including well-documented stock-related characteristics as well as option-related characteristics: firm size and book-to-market ratio (Fama and French (1993)), short-term reversal (Jegadeesh (1990), Lehmann (1990)), momentum (Jegadeesh and Titman (1993)), historical skewness (Harvey and Siddique (2000)), historical kurtosis, Amihud illiquidity (Amihud (2002)), maximum monthly return (Bali, Cakici, and Whitelaw (2011)), information asymmetry measured as option bid-ask spread, the level of implied volatility, the volatility skew (Xing et al. (2010)), and the option-to-stock volume ratio (Johnson and So (2012)). More importantly, the volatility tail risk effect doesn't get attenuated by idiosyncratic volatility (Ang et al. (2006)), and volatility-of-volatility effect (Baltussen et al. (2014)). But the reverse seems to be the case: the volatility-of-volatility effect is weakened when volatility tail risk comes into play. I also conduct rigorous tests to rule out the possibility that the negative cross-sectional predictability of volatility tail risk is merely driven by the renowned idiosyncratic volatility effect. Neither total volatility nor idiosyncratic volatility completely compromises stocks' volatility tail risk feature.

To test the debate between systematic and idiosyncratic VTR, I implement an individual stock VTR decomposition: I decompose stock-level VTR into systematic component, or $sVTR$, and idiosyncratic component, or $iVTR$, by projecting stock VTR onto the span of SPY VTR, which I use it as a proxy for market-level VTR, and constant. We show that the negative relation between VTR and future stock returns is primarily driven by systematic component in VTR measure. This validates the argument that the volatility tail risk is systematically priced in the cross-section of stock returns and the price of risk is negative. This can be explained by risk-compensation story: empirically, VTR tends to be high while the stock return is low. Consequently, an asset that pays off VTR is essentially a hedging asset to the economy, which should pay off with negative price of risk.

To guarantee that my volatility tail risk measure, VTR, effectively measures the fat tails of intraday IV distribution, I investigate the relation between VTR and other well-documented fat tail measures. I confirm that my volatility tail risk measure VTR is closely related to the traditional higher-order moment kurtosis. As a robustness check, I construct daily IV kurtosis measure from intraday IV data using method suggested by Amaya, Christoffersen, Jacobs, and Vasquez (2015). Amaya et al. (2015) shows in their paper that under realistic assumptions on the continuous dynamics of underlying equity prices (robust to stochastic volatility and jumps), the realized higher-order moments converge to well-defined limits. Building on this insight, the daily time-varying IV kurtosis is constructed using intraday quartic variations of log change in IV and then aggregated to monthly IV kurtosis for each stock separately. The second robustness check draws light from a recent paper by Kelly and Jiang (2014), where I fit a power-law distribution to the IV tail of each stock and estimate the daily volatility tail risk parameter of each stock using intraday IV distribution. The negative relation between volatility tail risk and expected stock returns in the cross-section is also confirmed using alternative measures of volatility tail risk. For example, a long-short strategy that buys stocks in the highest quintile of IV kurtosis and sells stocks in the lowest quintile of stocks yields an annual average Carhart (1997) four-factor alpha of -3.2% with a t-statistic of -1.76. The Fama and MacBeth (1973) regression result provides additional evidence by showing that IV kurtosis also negatively predicts subsequent stock returns in the cross-section after controlling for a battery of firm and option characteristics.

The rest of the paper is organized as follows. Section I summarizes related literature. Section II describes the data, especially the intraday option quotes from Nanex, and the construction and properties of the novel volatility tail risk measure. Section III establishes the validation and economic interpretations of the proposed volatility tail risk measure. I also validate in this section that the proposed VTR measure is one of the best predictor of future IV jumps. Section IV examines the effectiveness of alternative volatility tail risk measures. Section V presents empirical results on the relation between volatility tail risk and the cross-section of expected stock returns. Section VI examines the robustness of the proposed volatility tail risk measure from multiple aspects. Section VII concludes.

I. Literature Review

Finance literature that studies the measurement of tail properties and its impact on asset prices is of great volume. The measurement approach I use is closely related to Bollerslev and Todorov (2011), which studies the role of rare events in explaining equity risk premia and variance risk premia. Given a special structure of the diffusion and jump process, they identify and estimate a new Investor Fears Index. The index reveals large time-varying compensation for fears and disasters and shows that compensation for rare events accounts for a large fraction in variance risk premia. The measurement of volatility tail distribution is also related to Kelly and Jiang (2014) and Amaya et al. (2015). Kelly and Jiang (2014) uses a power-law approach to estimate the time-varying tail risk from a panel of tail returns of stocks. They show that their tail risk measure predicts aggregate stock market return up to five years. Amaya et al. (2015) estimates daily realized variance, skewness and kurtosis using intraday high-frequency return data. They conclude that realized skewness negatively predicts stock returns in the cross-section. A recent work by Begin, Dorion, and Gauthier (2017) shows that idiosyncratic jump risk matters. They have found that idiosyncratic factors explain almost 30% of the variation in the risk premium on a stock. And they show that the contribution of idiosyncratic risk to the equity risk premium arises exclusively from the jump risk component. They then conclude that tail risk thus plays a central role in the pricing of idiosyncratic risk. My paper contribute to this strand of literature by introducing a novel non-parametric (or semi-parametric) volatility tail risk measure that is immune to model misspecifications.

This paper is also related to research studying volatility-related risks and stock returns. Bakshi and Kapadia (2003) is one of the first set of papers studying the volatility risk premium through delta-hedged option returns. Within a stochastic volatility framework, they first demonstrated a correspondence between the sign and magnitude of the volatility risk premium and the mean of delta-hedged portfolio returns, and then provide strong evidence in supportive of a negative volatility framework. Bollerslev, Tauchen, and Zhou (2009) builds and examines the asset implications of a general equilibrium model incorporating the effects of time-varying economic uncertainty. They show that the variance risk premium is able to explain a non-trivial fraction of the time-series variation in post-1990 aggregate stock market returns. By incorporating volatility-of-volatility risk into the Bakshi and Kapadia (2003) framework, Huang and Shaliastovich (2014) shows that the volatility-of-volatility risk is a significant risk factor which affects both index and index option returns, and bears a negative price of risk. In contrast, Baltussen et al. (2014) studies the volatility-of-volatility effect and its impact on the cross-section of stock returns and argues that the negative volatility-of-volatility effect doesn't seem to be a systematic risk factor. Surprisingly, few people study how tail distribution of volatility process affects asset prices in the cross-section. I contribute to this strand of literature by exploring the importance of volatility tail risk in explaining the cross-section of stock returns as well as aggregate market return. I also show that the volatility-of-volatility effect (Baltussen et al. (2014)) may not be that robust and is dominated by the volatility tail risk effect in my sample.

The empirical methodology is built on a huge body of literature that studies the connections between stock characteristics and cross-section of stock returns. Those features include but not limited to firm fundamentals, stock return moments, as well as option-related characteristics. I briefly review the literature here. Fama and French (1992) shows that firm size and book-to-market equity capture the cross-sectional variation in average stock returns. Amihud (2002) documents that stock illiquidity affects the expected stock returns, and this illiquidity effect is stronger for small-cap stocks. Jegadeesh and Titman (1993) documents that a trading strategy that buys momentum portfolio earns significant positive return, and can't be explained by common risk factors. In addition to these first-order effects, Ang et al. (2006) provides evidence that exposure to aggregate market volatility is priced in the cross-section. Furthermore, they show that stock's idiosyncratic volatility relative to Fama and French (1993) negatively predicts future stock returns in the cross-section. This effect is extremely strong and economically large, and is not mitigated by other well-documented factors. Beyond that, Conrad et al. (2013) uses a panel of option prices to estimate the ex-ante risk-neutral volatility, skewness and kurtosis. They find a strong negative (positive) relation between ex-ante skewness (kurtosis) and subsequent stock returns. Amaya et al. (2015) uses intraday high-frequency data to examine the information contained in the realized higher-order moments and documents that realized skewness negatively predicts future stock returns in the cross-section.

Finally, this paper borrows insights from market microstructure literature that studies how information is incorporated into asset prices. Central to all information-based models is the role of informed traders and uninformed traders. Although specific modeling approaches differ, information gets incorporated into asset prices as a result of trading behavior of informed and uninformed traders. Glosten and Milgrom (1985) shows, in a sequential trading model, that trading can reveal information of underlying assets and affect the behavior of prices. This insight is enriched and pushed further by Easley, O'Hara, and Srinivas (1998), where they allow the participation of informed traders in the option market to be decided endogenously in an equilibrium framework. In their model, informed traders choose to trade in both the stock and the option market, in a pooling equilibrium, when option implicit leverage is high, when the stock market liquidity is low, or when the overall fraction of informed traders is high. Empirically, Pan and Poteshman (2006), taking advantage of a unique option data set by CBOE, presents strong evidence that option trading volume contains information about future stock prices. Consequently, their evidence clearly implies that the existence of informed trading in the option market.

II. Data and Empirical Design

In this section, I first describe the datasets used in this paper. Then I will show how the volatility tail risk measure, VTR, is defined and measured using the intraday high-frequency option quotes data from Nanex[2] and its conditional cross-sectional distribution by year-month. Finally, I construct portfolios by sorting stocks into quintiles based on monthly volatility tail risk measure, analyze VTR-portfolio characteristics and examine its performance.

[2]The intraday high-frequency option quotes data are obtained from Nanex, a high-quality data vendor. Nanex obtains its data from standard data aggregators: OPRA for options and SIP for equities (e.g. TAQ data in WRDS also use SIP).

A. Data

The Nanex option quotes database used in this paper contains data from January 2004 to December 2014. Nanex provides historical quotes, trades information for every option traded on a given day with 1-minute snapshots from 9:30 EST to 16:00 EST. Following Baltussen et al. (2014), and Xing et al. (2010), I use the implied volatility (IV) of at-the-money (ATM) options with closest to 30-day time-to-expiration to construct the intraday IV distribution of each stock. Particularly, for each 1-minute snapshot during trading hours, I select a group of options (both calls and puts) with $SK/S \in [0.95, 1.05]$ and time-to-maturity closes to 30 days, where S here stands for the closing price of a stock, and SK represents the strike price of an option. There are some papers also using $|\Delta| \approx 0.5$ as the definition of at-the-money (e.g. Bollen and Whaley (2004)). This turns out not to be an issue in my sample. Since my focus is on options with around 30-day time-to-expiration, those options with $SK/S \in [0.95, 1.05]$ will have $|\Delta| \approx 0.5$ in most of the cases. Such at-the-money IV estimates are generally based on the most liquid and informative option prices. To alleviate additional liquidity concerns, I further require that options, in order to be included in the sample, should have opening quotes in [9:30, 9:40] and closing quotes in [15:50, 16:00], and must have non-zero trading volume.

High frequency data usually contains some incorrect quotes, consequently, for each day, I apply the following filters to intraday option quotes in order to select out valid and reasonable option quotes data for the purpose of correctly computing intraday implied volatility of each stock: (1) Bid price $\leq$ Ask price. (2) Both bid price and ask price should exist. (3) Bid price is greater or equal to 10 cents. (4) Ask price is less than twice of the stock price. (5) (Bid-Ask)/Bid< 0.7 and (Bid-Ask)≤ 10 and (Bid-Ask)$\leq$Stock price. Condition (3) and (5) are used to rule out penny options, which are usually deep out-of-money options.

I use data of U.S.-listed options written on common equity shares of individual stocks traded on NYSE, NASDAQ or AMEX. To ensure sufficient liquidity, for daily stock file, I require that stock volume must be positive and stocks with closing price less than $1 are dropped. I also acquire data from three additional databases. I obtain daily and monthly stock return, volume, and shares outstanding data from Center for Research and Security Prices (CRSP) database to compute historical skewness (kurtosis), reversal, momentum, size, monthly maximum return and monthly Amihud illiquidity measure. Firm accounting data are extracted from Compustat. I obtain additional daily option data from OptionMetrics to compute the volatility-of-volatility used by Baltussen et al. (2014), the out-of-money skew in Xing et al. (2010), monthly average IV of at-the-money options and option liquidity, measured as option bid-ask spread. The final sample contains $156,509$ firm-month observations with approximately $1,500$ unique firms per year on average.

B. Construct Volatility Tail Risk Measure

I build the volatility tail risk measure of individual securities using IVs derived from intraday option prices, which are estimated from Black-Scholes formula. I first construct the daily volatility tail risk measure from intraday quadratic variations of the log change in IV for each stock, and then aggregate it to monthly volatility tail risk measure, VTR, by taking average across the month. The main advantage of using IV inferred from option price is that IV is a forward-looking measure of future realized volatility and reflects market participants' estimation of future uncertainty. Therefore, the volatility tail risk measure built from IV can be considered as an *ex-ante* measure of future volatility tail risk.

Taking a similar approach applied extensively in estimating the daily realized variance of stock returns (e.g.Andersen, Bollerslev, Diebold, and Labys (2003), Bollerslev and Todorov (2011)), I construct the daily realized variance of implied volatility of stock i on any given day j of month t as the summation of quadratic variations of the log change of intraday implied volatility:

$$RVV_{j,t}^{i} = \sum_{k=1}^{N}[dlog(\sigma_{k,j,t}^{IV,i})]^2, \tag{1}$$

where $dlog(\sigma_{k,j,t}^{IV,i}) = ln(\sigma_{k,j,t}^{IV,i}) - ln(\sigma_{k-1,j,t}^{IV,i}) = ln\left(\frac{\sigma_{k,j,t}^{IV,i}}{\sigma_{k-1,j,t}^{IV,i}}\right)$. Here, N is the number of intraday log change in IV recorded on day j. For the Nanex dataset, the 1-minute snapshot means $N = 390$. As a standard approach, I do not adjust for the mean here because in high-frequency world, variance dominates.

The construction of the daily left-tail (right-tail) variation of implied volatility, $RLTVV_{j,t}^{i}$

($RRTVV^i_{j,t}$), is a variation of the method proposed by Bollerslev and Todorov (2011).

$$RLTVV^i_{j,t} = \sum_{k=1}^{N} [dlog(\sigma^{IV,i}_{k,j,t})]^2 1_{\{dlog(\sigma^{IV,i}_{k,j,t}) < \alpha^{L,i}_{j,t}\}}, \tag{2}$$

$$RRTVV^i_{j,t} = \sum_{k=1}^{N} [dlog(\sigma^{IV,i}_{k,j,t})]^2 1_{\{dlog(\sigma^{IV,i}_{k,j,t}) > \alpha^{R,i}_{j,t}\}}, \tag{3}$$

where $1_{\{\cdot\}}$ is a indicator function and equals to 1 if the condition in $\{\cdot\}$ is true. $\alpha^{L,i}_{j,t}$ ($\alpha^{R,i}_{j,t}$) is the left-tail (right-tail) threshold of $dlog(\sigma^{IV,i}_{k,j,t})$. However, my choice of $\alpha^{L,i}_{j,t}$ ($\alpha^{R,i}_{j,t}$) is different from Bollerslev and Todorov (2011). The purpose of $RLTVV^i_{j,t}$ ($RRTVV^i_{j,t}$) is to capture the left-tail (right-tail) component of the daily realized variance of implied volatility. Therefore, I do not need extreme-value theory to specifically identify rare "jumps" as what Bollerslev and Todorov (2011) does in their paper. Therefore, I choose the $\alpha^{L,i}_{j,t}$ to be the 5% value of $dlog(\sigma^{IV,i}_{k,j,t})$'s intraday distribution, and $\alpha^{R,i}_{j,t}$ to be the 95% value of $dlog(\sigma^{IV,i}_{k,j,t})$'s intraday distribution for each stock i separately. Figure 1 gives an illustrative example of how I choose the left-(right-) tail distribution given the probability density function of $dlog(\sigma^{IV})$.

[Place Figure 1 about here]

I construct the daily tail variation of implied volatility, $RTVV^i_{j,t}$, of each stock i as the summation of $RLTVV^i_{j,t}$ and $RRTVV^i_{j,t}$:

$$RTVV^i_{j,t} = RLTVV^i_{j,t} + RRTVV^i_{j,t}. \tag{4}$$

The interpretation of this measure is quite straight-forward: $RTVV^i_{j,t}$ captures the 10% *most* fat-tailed component of $dlog(\sigma^{IV,i}_{k,j,t})$'s intraday distribution. It can be seen that I don't add overnight change in log-IV to the $RTVV$ measure here. Drop the overnight period can avoid the IV drop during firm's earning announcements. Consequently, it makes sure that VTR is not contaminated by earning announcement effects. Meanwhile, in the literature, it is not clear whether overnight period contains valuable information or simply adds more noise.

To alleviate micro-structure noise concerns, I then aggregate these daily volatility tail risk measures to monthly volatility tail risk measures by taking average. The monthly realized variation of volatility of stock i in month t is defined as: $RVV_t^i = \frac{1}{N_t}\sum_{j=1}^{N_t} RVV_{j,t}^i$, where N_t is the number of daily observations in month t. Since $RTVV_{j,t}^i$ would tend to be large if $RVV_{j,t}^i$ is large, the monthly volatility tail risk measure, VTR, is built by scaling RVV to filter out the level effect. Mathematically,

$$VTR_t^i = \frac{1}{N_t}\sum_{j=1}^{N_t} \frac{RTVV_{j,t}^i}{RVV_t^i}, \tag{5}$$

where RVV_t^i is defined above. In fact, my volatility tail risk measure VTR_t^i bears similar intuition as statistical higher-order moment: kurtosis. However, compared with kurtosis measure, my measure is more focused on tail distribution of implied volatility. I will also use IV Kurtosis as an alternative measure of volatility tail risk in Section IV. In addition, the value of this scaled volatility tail risk measure, VTR_t^i, will definitely fall in [0, 1] for stock i on any given month t. To guarantee sufficient liquidity for this measure, I require a minimum of $N_t = 5$ daily observations for a given month t.

Similarly, I can also define the monthly left-tail (right-tail) risk measure of volatility as:

$$VLTR_t^i = \frac{1}{N_t}\sum_{j=1}^{N_t} \frac{RLTVV_{j,t}^i}{RVV_t^i} \tag{6}$$

$$VRTR_t^i = \frac{1}{N_t}\sum_{j=1}^{N_t} \frac{RRTVV_{j,t}^i}{RVV_t^i} \tag{7}$$

Consequently, we will have the following identity: $VTR_t^i = VLTR_t^i + VRTR_t^i$. Furthermore, from now on, I will suppress the superscript and subscript in notation VTR_t^i if no confusion would occur.

There are multiple advantages that allow my proposed measure, VTR, to serve as a good proxy on measuring volatility tail risks: (1) first and foremost, the advantage of using non-parametric measure, in contrast to parametric measure (i.e. complex structural models), is that non-parametric approach is immune to model misspecifications. Frankly speaking, unlike experimental science, it is hard to testify the validity of a model. Furthermore, structural models with both jumps in stock return and volatility, as well as stochastic volatility process (multiple hidden factors), make the accurate estimation of parameters a tough task even with MH algorithm and Gibbs sampling. (2) Second, the reason for using high-frequency quadratic variations is motivated Bollerslev and Todorov (2011). In their paper, they discuss that if we assume that stock return process is comprised of a diffusion component and a jump component, then the tail variation of intraday quadratic variation can be a reliable measure of realized jumps in intraday stock returns. Furthermore, the assumption that volatility follows from geometric Brownian motion is also widely used in finance literature, for example, Huang and Shaliastovich (2014). Therefore, given the mathematical inductions in Bollerslev and Todorov (2011), I argue that the VTR measure in my paper can reasonably capture tail variations in intraday IV change. (3) Third, comparing our measure to kurtosis measure, which is an extensively used measure for estimating tail distribution in statistics, the major difference comes from the numerator part. The part in curly braces, $\{dlog(\sigma_{k,j,t}^{IV,i}) < \alpha_{j,t}^{L,i}\} + dlog(\sigma_{k,j,t}^{IV,i}) > \alpha_{j,t}^{R,i}\}$, ensures that we only capture large tail variations (jump components) in IV process, while traditional kurtosis measure, IVKurt, doesn't really separate them out. Hence, for the purpose of the paper, VTR is a better fit.

[Place Table I about here]

In Table I, I present descriptive statistics of VTR by year. I report means, standard deviations, medians as well as 10th, 25th, 75th and 90th percentiles over time and across securities for each year during the sample period. The cross-sectional percentiles suggest that the IV distribution of individual stock is quite *fat-tailed*, as we can see that the means and medians are usually greater than 0.65 over time, the average of which are 0.6955 and 0.6875 respectively. This suggests that the volatility tail risk should be a non-trivial priced risk factor and deserves a careful examination. Moreover, the 10th percentile of VTR is consistently higher than 0.5 across years, further reinforcing the fat-tail property of individual stock volatility distribution.

[Place Figure 2 about here]

In Figure 2, I plot the 10th, 25th, Median, 75th and 90th percentiles of VTR across securities for each year-month. There are some interesting patterns reflected in Figure 2. First, we observe a sharp decline in VTR of all percentiles by the end of 2008. This suggests that the whole cross-sectional distribution of VTR moves left towards the origin. This is pretty interesting because this time period is when the 2008 financial crisis got worse. We might expect more fat-tailed distribution of VTR rather than less. As a robustness check, I also check the possibility of miscalculation by examining the cross-sectional distribution of IV kurtosis (See Figure 7). The IV kurtosis graph confirms that this is not a miscalculation issue. My interpretation to this decline is that the whole distribution of VTR became more dispersed around crisis. This is confirmed by Baltussen et al. (2014) that the volatility-of-IV actually increased in 2008, which is also true in my sample period. As a consequence, either VTR or IV kurtosis turns out to be smaller due to scaling. Second, we observe an increasing trend in VTR starting from the end of 2013. Broadly speaking, the cross-sectional distribution of VTR is generally stable across the sample period except for the 2008 financial crisis period, where the IV distribution of individual stock was extremely volatile.

C. Characteristics of VTR-Sorted Portfolios

By the end of each month, I sort stocks into equal-weighted quintile portfolios based on the monthly volatility tail risk measure, VTR. Table II reports the time-series average of VTR and firm characteristics, by quintile. Column 1 contains portfolio of stocks with the lowest VTR and column 5 contains portfolio of stocks with the highest VTR. Firm characteristics include equity return jump measure (ERJM), volatility risk premium (VRP), the log of firm size (Size)(in $billions), the log of book-to-market ratio (LBM)(Fama and French (1993)), short-term reversal (Reversal) and long-term momentum (Momentum)(Jegadeesh (1990), Jegadeesh and Titman (1993)), historical skewness (HSkew)(Harvey and Siddique (2000)), historical kurtosis (HKurt), monthly maximum return (MaxRet), Amihud illiquidity measure (Amihud)(Amihud (2002)), option quoted spread (OptSpread), monthly average implied volatility (ImpVol), OTMSkew (also known as volatility skew in Xing et al. (2010)).

[Place Table II about here]

From Table II, we can observe that VTR moves from an average of 0.564 in quintile 1 to an average of 0.847 in quintile 5. And there exists a strong pattern between VTR and some firm characteristics: (1) firm size is negatively correlated with VTR. This turns out to be the case mainly because small cap-stocks are generally more volatile than large cap-stocks. The volatility of small cap-stock is more volatile as well. Consequently, small cap-stocks usually bear high VTR. (2) High VTR stocks tend to be less liquid: both measured by stock illiquidity, Amihud, and option illiquidity, OptSpread. I will show that VTR captures future illiquidity information but is not fully driven by illiquidity. The interaction between VTR and illiquidity is analyzed in detail in next section. (3) VTR is also positively correlated with stock volatility, i.e. idiosyncratic volatility, though not very pronounced. We show in later section that the negative relation between VTR and future stock returns can be partially explained by the idiosyncratic volatility relation documented by Ang et al. (2006).

A formal test of the unconditional correlation between VTR and firm characteristics is reported in Table XII Panel B. Detailed discussion and double-sorting analysis will be conducted in Section VI to further disentangle VTR effect from other mixed features.

III. Validations and Interpretations

On introducing a novel volatility tail risk measure, I plan to validate this measure from multiple aspects. First, I analyze the connection between volatility tail risk and equity return jump measure, $ERJM$. I show that volatility jumps and stock return jumps is empirically uncorrelated and for SPX series: the correlation is merely *0.01* with no statistical significance. I also test the market return predictability using VTR, $ERJM$, VRP (volatility risk premium) and dividend-price ratio (or D/P). I show that VTR negatively predict future stock return even after controlling for other predictors.

Then, I compare the relation between VTR and other crucial firm characteristics. In particular, to make economic magnitudes comparable, I standardize each variable to zero mean and unit variance. I first conduct a VTR explanatory analysis by regressing VTR on other firm features (contemporaneously). I also examine how VTR is related to future economic state variables by testing its capability in forecasting future macro quantities through VAR analysis. Finally, I examine whether VTR is an effective predictor of future IV jumps by predicting future IV jump measures, i.e. IVJI/IVJS/IVSJS, using lagged VTR and other crucial variables.

In the model proposed by Broadie et al. (2007), they show that jumps in stochastic process can affect the pricing of options. To examine this implication, we explore the relation between VTR and subsequent option returns, measured by option straddle returns and variance risk premium. The variance risk premium is approximated by the difference between implied volatility and realized volatility.

A. *Stock Market Return, VTR and $ERJM$*

To examine the relation between volatility tail risk and stock return tail risk, we construct stock return jump measure, or $ERJM$, based on the measure proposed by Bollerslev and Todorov (2011). In particular, I highlight the time-series of CRSP value-weighted stock market return, VTR and $ERJM$ constructed from SPY in the figure below.

[Place Figure 4 about here]

In Figure 4, I address 2 important questions here: first, how correlated is volatility jump and stock return jump? The time-series Pearson correlation between VTR and $ERJM$ of SPY is: 0.01, which is literally not significant at all. Namely, we don't observe statistically significant correlation between jumps in return and jumps in volatility. This is not surprising: in finance literature, as suggested by many papers that study sophisticated structural models, i.e. Eraker et al. (2003), they assume that the jump process in return and volatility are mutually independent.

Second, why we don't see a spike in VTR? From the figure above, I want to argue the following fact: realized volatility spike doesn't necessarily imply that it is caused by a jump in volatility process. It can also be driven by jump in underlying stock return. i.e. thinking about GARCH-style volatility models. That is exactly what we saw in the 2008 Crisis period. The volatility swings during 2008 financial crisis period are mostly driven by jump events in underlying stock return that are illustrated in the bottom panel. Furthermore, this also confirms the low correlation between VTR and $ERJM$.

[Place Table VI about here]

In Table VI, I test the market return predictability at different horizons: 1-month, 3-month, and 6-month. There are good things and bad things in this market return predictability test. The good thing is: consistent with findings in the cross-section, VTR negatively predicts future market return. However, the bad thing is: the statistical power is not very strong.

As we acknowledge this deficiency in time-series test, the reasons could be multi-dimensional:

- The sample for our test is just not long enough. We only have 104 monthly observations. In a time-series test, this is not quite sufficient.

- Our measure is a proxy of systematic volatility tail risk using SPY. Henceforth, measurement error could be an issue.

It is also interesting to see that in the joint regression, VRP is probably the only significant variable: the reason is because VRP is measured as IV-RV. In a model with both jumps in stock return and volatility, VRP captures three effects: pure variance risk, stock return jump risk, and volatility jump risk.

B. *How Important is VTR?*

In this part, I want to address the following important question: how important is the information captured by VTR? Namely, if the information contained in VTR can be fully explained by other firm characteristics and factors, then VTR is redundant from the perspective of asset pricing.

To address this issue and make estimated coefficients comparable, I first standardize each variable to zero mean and unit variance. The advantage of using standardized variable is that the economic impact on VTR of each variable is directly comparable from the magnitude of the coefficient.

[**Place Table III about here**]

In Table III, the four variables that have the most impact on VTR in univariate regression are: ERJM, Size, Amihud, and OptSpread. We further classify them into 3 categories: stock return jump risk (ERJM), firm size (Size) and liquidity risk (Amihud, and OptSpread).

[**Place Figure 5 about here**]

Results in Figure 5 show the cross-sectional explanatory power of each variable: only Size, Amihud, and OptSpread have over 10% R-square. Furthermore, all variables can only explain around 30% of total cross-sectional variation in VTR, which indicates that VTR captures additional non-trivial information that is not captured by other variables. In other words, most of the information in VTR is not captured by other firm characteristics and factors.

C. VAR Analysis

In this section, I implement VAR analysis to explore the connection between VTR and future economic activities. In macroeconomics, one important research topic is to investigate predictors that can effectively forecast future macroeconomic activities. Therefore, I show that the proposed VTR measure not only captures exclusive information contemporaneously, but also predicts future economic quantities.

In particular, we run the following predictive regressions:

$$X_{t+1}^{i} = \alpha + \beta' X_t^i + \epsilon_{t+1}^{i}, \tag{8}$$

where X_t^i is a vector of economic state variables including all related variables and factors.

[Place Table IV about here]

First, in order to validate VTR measure in a comprehensive way, variables that are closely related to VTR must be considered in a careful way, i.e. equity return jump measure (ERJM), volatility risk premium (VRP), and liquidity measure (Amihud and OptSpread). Similarly, to make magnitudes comparable, all variables are standardized to zero mean and unit variance.

Results in Table IV show that VTR has quite decent persistency and statistical power. The cross-sectional autocorrelation, after controlling for other lagged factors, is *0.44*. Meanwhile, we also confirm the interaction between stock return jump (ERJM) and volatility jump (VTR): albeit VTR positively predicts ERJM in next period, the impact magnitude is not impressive, merely *0.02*. And, ERJM positively predicts future VTR, but with little statistical power. Furthermore, it positively and robustly predicts future volatility risk premium, idiosyncratic volatility, stock return high-order moments, illiquidity measures and volatility skew.

D. VTR and IV Jumps

To provide an incisive and clear picture of the relation between the proposed IV tail risk measure, VTR, and IV jumps, we construct several IV jump measures using a robust non-parametric identification approach proposed by Lee and Mykland (2007). The formal mathematical theorems are described in details in Appendix B. The intuition of this methodology is that if the stochastic volatility process consists of a diffusion component and a jump component, then we can identify a deviation as a jump with certain confidence level if the magnitude of this deviation is way-too-large compared with conditional bi-power variation.

I extend this idea by further compute statistics based on identified IV jumps at 99% confidence level. Three IV jump measures are constructed: IVJI, IVJS and IVSJS. IVJI stands for IV jump intensity. IVJS stands for IV jump size. IVSJS stands for IV scaled jump size. Mathematically, for any stock i on any given day j of month t,

$$IVJI^i_{j,t} = \frac{1}{N}\sum_{k=1}^{N} 1_{\{dlog(\sigma^{IV,i}_{k,j,t}) \in \{Jumps\}\}}, \tag{9}$$

$$IVJS^i_{j,t} = \frac{1}{NJ}\sum_{k=1}^{N} |dlog(\sigma^{IV,i}_{k,j,t})| \cdot 1_{\{dlog(\sigma^{IV,i}_{k,j,t}) \in \{Jumps\}\}}, \tag{10}$$

$$IVSJS^i_{j,t} = \frac{1}{NJ}\sum_{k=1}^{N} \frac{|dlog(\sigma^{IV,i}_{k,j,t})|}{|\overline{dlog}(\sigma^{IV,i}_{k,j,t})|} \cdot 1_{\{dlog(\sigma^{IV,i}_{k,j,t}) \in \{Jumps\}\}}, \tag{11}$$

where $1_{\{\cdot\}}$ is an indicator function and equals 1 if the condition in $\{\cdot\}$ is true, and NJ is the number of jumps identified per day: $dlog(\sigma^{IV,i}_{k,j,t}) \in \{Jumps\}$. N is number of intraday periods: for our sample, $N = 390$. $|\overline{dlog}(\sigma^{IV,i}_{k,j,t})| = \frac{1}{N}\sum_{k=1}^{N} |dlog(\sigma^{IV,i}_{k,j,t})|$, represents the average absolute variation of $dlog(\sigma^{IV,i}_{k,j,t}$. From the construction we can see that IVJS measure is contaminated by the diffusion variation. Therefore, the purpose of IVSJS is to mitigate the effect of diffusion component when measuring the IV jump size property. Daily measures of $IVJI^i_{j,t}$, $IVJS^i_{j,t}$, and $IVSJS^i_{j,t}$ are then aggregated to monthly level by taking average for each stock i to obtain $IVJI^i_t$, $IVJS^i_t$, and $IVSJS^i_t$. In Figure 3, we plot the cross-sectional distributions of these three IV jump measures. Compared with the cross-sectional distribution of VTR in Figure 2, we find strong comovements between VTR and IVJI/IVSJS. This provides preliminary evidence that our IV tail risk measure VTR really measures jump components in the intraday IV process.

[**Place Figure 3 about here**]

Before dealing with the correlation issue, we first explain what IVJI means. For example, $IVJI = 0.01$ means: we identify 1 jump out of 100 intraday observations. Consequently, since we observe 390 observations per day, $IVJI = 0.01$ would mean that we identify 390*0.01=3.9 jumps per day. That is what I call as "IV jump intensity". In Table V, I report the unconditional cross-sectional correlation between VTR and IV jump measures IVJI/IVJS/IVSJS. The correlations with all 3 IV jump measures are quite decent and *statistically significant*. Meanwhile, we need to be aware that given the rarity of jump events, the historical IV jump intensity measure may not be that accurate.

[Place Table V about here]

The Table V Panel B reports the cross-sectional forecasting regressions of IV jump measures constructed from realized IV process. First of all, each variable is standardized to zero mean and unit variance. Consequently, we can compare the economic magnitude of each explanatory variable directly. While controlling for all other important variables, we can observe that VTR is still the most effective predictor of future IV jumps: VTR generates the highest average coefficient (0.207) across all three IV jump measures as well as t-statistics.

In terms of model fitness, the univariate average R-square of only using VTR is about 15%, while using all variables can merely explains about 30% of total cross-sectional variation in VTR. This indicates that VTR is as important as all other factors in predicting future IV jumps. This serves as a piece of strong evidence that the proposed volatility tail risk measure, VTR, has a better capability of forecasting future IV jump risks over other variables.

E. VTR and Liquidity Concern

As we find in subsection III.B, liquidity is one of the most important factors that affects the validity of VTR measure. I address the liquidity concern from two aspects: stock liquidity (i.e. Amihud) and option liquidity (i.e. option quoted spread, or OptSpread).

In the paper, to alleviate microstructure noise concern, I use 3 approaches: first, the IV is constructed from around 30-day ATM option, which is known for good liquidity condition. Second, I smooth the VTR measure across days in a month to form monthly measures. Third, I also control for these illiquidity measures in regressions.

The concern that VTR may capture illiquidity rather than IV jump information is resolved in subsection **?**. We show that even controlling for illiquidity measures, VTR is still the most effective predictor of future IV jumps. Besides, VTR itself is quite persistent, which indicates that VTR has at least one persistent component that varies over time, and is not temporary noise.

[Place Figure 6 about here]

To address some of the concerns that the negative relation is driven by illiquidity, we conduct double-sorting from the perspective of stock and option liquidity respectively. The double-sorting strategy is implemented in a conditional approach: we first sort stocks based on Amihud (Opt-Spread), then sort stocks based on VTR measure.

The upper left panel shows the double-sorting portfolio performance for Amihud and VTR, it is obvious that we can observe statistically and economically significant and negative relation in almost all quintile groups (4 out of 5). And in particular, albeit the long-short portfolio of the 5th Amihud group generates the largest negative alpha, we don't observe a particular strong linear pattern that the negative relation in VTR is driven by stock illiquidity.

The double-sorting result on stock liquidity is further reinforced by the double-sorting result on option liquidity, measured by OptSpread. The average long-short magnitude for OptSpread quintile group 2 to 5 is about -1%. And the pattern is pretty much flat, which rules out the hypothesis that the negative relation in VTR is driven by option market illiquidity.

F. VTR, Option Returns and Variance Risk Premium

In the paper by Broadie et al. (2007), they examine the model specification issues and estimate diffusive and jump risk premia using S&P futures and futures options. They find strong evidence in support of the presence of jumps in volatility in a time-series test. As an alternative approach, they also find modest evidence of jumps in volatility using cross-section of option prices.

In this subsection, I examine how my volatility tail risk measure VTR affects the cross-section of option returns and variance risk premium. To eliminate first-order stock price movements, we use delta-neutral option straddle return: for each call option, we choose one put option with same strike and expire date and such that the pair of option portfolio is risk neutral. Then we take an equal-weighted approach for options with moneyness (measured as option delta) in $[0.35, 0.65]$ for each stock each day. We use $OptRet_{avg}^{straddle}$ to represent average daily option straddle return for each stock in a given month, and use $OptRet_{sum}^{straddle}$ to represent aggregated option straddle return for each stock in a given month. Bollerslev et al. (2009) show that under certain structural assumptions, variance risk premium can be represented as: $VRP = IV - RV$, where IV is implied volatility and RV is realized volatility. In this paper, RV is the annualized daily volatility computed from daily returns of a given month.

[Place Table VI about here]

As displayed in Table VI, we can conclude that VTR does affect option prices: specifically, VTR positively predicts cross-section of option straddle returns. Admittedly, a 1.8 t-value is not very impressive. But given the volatile nature of option returns and limited sample size, the 10% statistical significance is acceptable. In addition, we show that VTR strongly predict cross-sectional $VRP = IV - RV$, which is consistent with results in Table V.

We can arrive at several conclusions here: (1) since the delta-neutral option straddle rules out most of the variations in stock prices, we show that the volatility tail risk measure, VTR, is priced in the cross-section of option returns. (2) We show that a certain fraction of the variance risk premium measure, $VRP = IV - RV$, can be attributed to volatility tail risks. (3) Together with results in subsection III.C, we conclude that the proposed volatility tail risk measure, or VTR, contains valuable information about future economic activities and IV jumps, and are priced in the option market.

IV. Alternative Measures

The volatility tail risk measure, VTR, which I propose in Section II.B is novel and immune to model misspecifications albeit not very intuitive. To ensure that my volatility tail risk measure, VTR, essentially measure the fat-tail risk of volatility process, I consider two well-documented alternative measures here: (1) the first measure is kurtosis. Amaya et al. (2015) provides theoretical foundations for estimating daily kurtosis using high-frequency data. (2) The second measure is a well-documented tail risk measure induced by power-law method, which is proposed by Kelly and Jiang (2014). I show, in this section, that VTR is highly correlated with these two alternative measures, and they share some common properties.

A. IV Kurtosis (IVKurt)

The IV Kurtosis measure, IVKurt, built in this part follows the method used by Amaya et al. (2015). Specifically, I construct the daily kurtosis of volatility for stock i on any given day j of month t as:

$$IVKurt^i_{j,t} = \frac{N \sum_{k=1}^{N} [dlog(\sigma^{IV,i}_{k,j,t})]^4}{[RVV^i_{j,t}]^2}, \tag{12}$$

where $dlog(\sigma^{IV,i}_{k,j,t}) = ln(\sigma^{IV,i}_{k,j,t}) - ln(\sigma^{IV,i}_{k-1,j,t}) = ln\left(\frac{\sigma^{IV,i}_{k,j,t}}{\sigma^{IV,i}_{k-1,j,t}}\right)$. Here, N is the number of intraday log change in IV recorded on day j. The $RVV^i_{j,t}$ is the daily realized variation of volatility defined in II.B. Amaya et al. (2015) proves that under realistic assumptions, this realized high-order moment converges to well-defined limits. The limit of IVKurt is determined by jumps in the continuous-time process. Under the setting of this paper, IVKurt is dominated by jumps in the intraday IV process.

Similar to the aggregation process I use for VTR construction, the daily $IVKurt^i_{j,t}$ is then aggregated to monthly $IVKurt^i_t$ by taking average across days in month t for each firm i separately. Mathematically,

$$IVKurt^i_t = \frac{1}{N_t} \sum_{j=1}^{N_t} IVKurt^i_{j,t}, \tag{13}$$

where N_t is the number of daily observations in month t.

I also construct the IV skewness measure, IVSkew, using intraday IV data following the procedure in Amaya et al. (2015). The daily skewness of volatility for stock i on any given day j of month t is defined as:

$$IVSkew^i_{j,t} = \frac{\sqrt{N} \sum_{k=1}^{N} [dlog(\sigma^{IV,i}_{k,j,t})]^3}{[RVV^i_{j,t}]^{3/2}}. \tag{14}$$

and monthly IV skewness measure is defined as: $IVSkew^i_t = \frac{1}{N_t} \sum_{j=1}^{N_t} IVSkew^i_{j,t}$.

The IVSkew measure is not my primary interest here. The purpose I include this one is to control the potential skewness effect. One caveat is that IVSkew is different from the OTMSkew used by Xing et al. (2010). In Xing et al. (2010), they call OTMSkew as volatility skew, which is defined as the difference between out-of-monney put IV and at-the-money call IV with time-to-maturity in [10, 50] days. The OTMSkew measure is primarily affected by excess tail risks in underlying stock returns, which is quite different from the information captured by IVSkew. Figure 7 plots the cross-sectional percentiles of IVKurt by year-month. Broadly speaking, we can observe similar patterns as the cross-sectional percentiles of VTR in Figure 2, which provides evidence in support of the high correlation between these two measures. The formal test of unconditional correlation is shown in Table VIII Panel A.

[Place Figure 7 about here]

B. Power-Law Method: λ^{LT} and λ^{RT}

The second alternative measure I use is a variation of the tail risk measure proposed by Kelly and Jiang (2014) [3]. The empirical framework of Kelly and Jiang (2014) is built on a reduced-form description for the tail distribution of returns. They assume that the lower tail of asset returns behaves in a similar power law fashion. Specifically, in my setting, the left-tail distribution of the log change of intraday IV for firm i on any given day j of month t is defined as:

$$Prob(dlog(\sigma_{k,j,t}^{IV,i}) < x \ \mid \ dlog(\sigma_{k,j,t}^{IV,i}) < \mu_{j,t}^{LT,i}, F_{j,t}) = \left(\frac{x}{\mu_{j,t}^{LT,i}}\right)^{-\frac{1}{\lambda_{j,t}^{LT,i}}}, \tag{15}$$

where $x < \mu_{j,t}^{LT,i} < 0$, and $F_{j,t}$ is the information set at time (j,t). $\mu_{j,t}^{LT,i}$ is the left-tail threshold. The choice of $\mu_{j,t}^{LT,i}$ follows from II.B, $\mu_{j,t}^{LT,i} = \alpha_{j,t}^{L,i}$ to be the 5% value of $dlog(\sigma_{k,j,t}^{IV,i})$'s intraday distribution (This choice is also what Kelly and Jiang (2014) use). Equation 15 states that the extreme $dlog(\sigma_{k,j,t}^{IV,i})$ events obey a power law. The parameter of the model, $\lambda_{j,t}^{LT,i}$, determines the shape of of the tail and is referred to as the tail component. Since $x < \mu_{j,t}^{LT,i} < 0$ and $x/\mu_{j,t}^{LT,i} > 1$, the probability of tail events $\left(\frac{x}{\mu_{j,t}^{LT,i}}\right)^{-1/\lambda_{j,t}^{LT,i}}$ gets bigger if $\lambda_{j,t}^{LT,i}$ is larger. The time-varying $\lambda_{j,t}^{LT,i}$ is referred to as the "left-tail risk" of firm i at time (j,t).

Given the panel of observations of $dlog(\sigma_{k,j,t}^{IV,i})$ on any given day j for firm i, the daily $\lambda_{j,t}^{LT,i}$ is estimated through Hill (1975)'s power law estimator. Mathematically,

$$\lambda_{j,t}^{LT,i} = \frac{1}{K}\sum_{k=1}^{K} ln\left(\frac{dlog(\sigma_{k,j,t}^{IV,i})}{\mu_{j,t}^{LT,i}}\right), \tag{16}$$

where K is the total number of exceedences where $dlog(\sigma_{k,j,t}^{IV,i}) < \mu_{j,t}^{LT,i}$ on any given day j of month

[3] Albeit we operate under similar power-law framework, the assumption I use differ slightly from Kelly and Jiang (2014). In their paper, stocks have similar tail distribution and the tail risk $\lambda_t^i = \lambda_t$ across stock universe. Finally, they infer λ_t from the cross-sectional tail events of individual stocks.

t for firm i. Then, I aggregate this daily $\lambda_{j,t}^{LT,i}$ to $\lambda_t^{LT,i}$ of month t for each firm i separately:

$$\lambda_t^{LT,i} = \frac{1}{N_t} \sum_{j=1}^{N_t} \lambda_{j,t}^{LT,i} \tag{17}$$

where N_t is the number of daily observations in month t.

The "right-tail risk" parameter $\lambda_{j,t}^{RT,i}$ can be defined similarly. Specifically, I assume the right-tail distribution of the log change of intraday IV for firm i on any given day j of month t follows:

$$Prob(dlog(\sigma_{k,j,t}^{IV,i}) > x \ \mid \ dlog(\sigma_{k,j,t}^{IV,i}) > \mu_{j,t}^{RT,i}, F_{j,t}) = \left(\frac{x}{\mu_{j,t}^{RT,i}} \right)^{-\frac{1}{\lambda_{j,t}^{RT,i}}}, \tag{18}$$

where $x > \mu_{j,t}^{RT,i} > 0$, and $F_{j,t}$ is the information set at time (j,t). $\mu_{j,t}^{RT,i}$ is the right-tail threshold. The choice of $\mu_{j,t}^{RT,i}$ is the 95% value of $dlog(\sigma_{k,j,t}^{IV,i})$'s intraday distribution. The Hill (1975)'s power law estimator for the "right-tail" risk parameter $\lambda_{j,t}^{RT,i}$ is:

$$\lambda_{j,t}^{RT,i} = \frac{1}{K} \sum_{k=1}^{K} ln \left(\frac{dlog(\sigma_{k,j,t}^{IV,i})}{\mu_{j,t}^{RT,i}} \right) \tag{19}$$

where K is the total number of exceedences where $dlog(\sigma_{k,j,t}^{IV,i}) > \mu_{j,t}^{RT,i}$ on any given day j of month t for firm i. Then, aggregate $\lambda_{j,t}^{RT,i}$ to monthly "right-tail risk" measure for firm i:

$$\lambda_t^{RT,i} = \frac{1}{N_t} \sum_{j=1}^{N_t} \lambda_{j,t}^{RT,i} \tag{20}$$

where N_t is the number of daily observations in month t. Furthermore, from now on, the superscript i and the subscript t will be suppressed if not necessary.

[Place Table VIII about here]

Having defined the alternative measures, I then test the correlation between VTR and these alternatives. Table VIII Panel B reports the unconditional correlations of different volatility tail risk measures. The correlations of VTR with IVKurt, λ^{LT} and λ^{RT} are 0.668, 0.678 and 0.687, respectively. The evidence in Table VIII Panel A shows that my volatility tail risk measure, VTR, is highly correlated with other well-documented tail risk measures. High correlations also suggest

VTR should be able to capture excess volatility tail effectively.

V. Stock Return Predictability

In this section, I examine the relation between VTR and future monthly stock returns in the cross-section. Subsequently, I study the economic magnitude and performance persistence of the long-short portfolio which buys stocks in the highest quintile $Q5$ and sells stocks in the lowest quintile $Q1$. Finally, I formally test the negative relation between VTR and the cross-section of future stock returns through Fama-MacBeth (Fama and MacBeth (1973)) cross-sectional regressions. I also test the robustness of the VTR effect against a battery of control variables. Finally, I decompose VTR into systematic VTR, $sVTR$, and idiosyncratic VTR, $iVTR$, by projecting individual stock VTR onto SPY VTR (systematic VTR proxy). I validate that the negative relation between stock and future stock returns is primarily driven by systematic VTR components rather than idiosyncratic components. This implies that volatility tail risk is priced as a systematic risk factor with negative price of risk.

A. Portfolio Sorts

At the end of each month, stock are ranked into quintiles based on VTR. Then equal-weighted portfolios are formed and portfolio returns in next month are computed and recorded. Table IX Panel A reports the time-series averages of monthly returns for VTR quintile portfolios.

[Place Table IX about here]

In Table IX Panel A, we can observe a decreasing trend between the level of VTR and the average return in subsequent month. The average monthly return decreases from 68.3 basis points for the lowest quintile portfolio to 24.7 basis points for the highest quintile portfolio. The "High-Low" strategy that buys stocks in the highest quintile and sells stocks in the lowest quintile generates an average raw return of -43.6 basis points per month, which is -5.23% per annum. The t-statistic associated with the High-Low portfolio is -2.405, which is statistically significant at 5% level. I also adjust the average raw return by standard measures of systematic risks. The CAPM alpha, adjusting for excess market return, of the High-Low portfolio is -47.6 basis points per month

(-5.71% per annum) with a t-statistic of -2.737. The FF3 alpha, adjusting for excess market return, small-minus-big, high-minus-low, equals -44.8 basis points per month (-5.38% per anuum) with a t-statistic of -2.715. The FF3+MOM alpha, which adjusts for Fama-French three factors (Fama and French (1993)) as well as Carhart momentum factor (Carhart (1997)), equals -42.2 basis points per month (-5.1% per annum) with a t-statistic of -2.665, statistically significant at 1% level. Both raw return and risk-adjusted alpha results show that the negative relation between VTR and the cross-section of subsequent stock returns is economically and statistically significant.

To get a more straight-forward view of this negative relation, I plot a bar graph that displays the average raw excess return and the Carhart (1997) four-factor alpha of VTR-sorted quintile portfolios as well as the High-Low portfolio in Figure 8. The unit of vertical axis is percentage. Broadly speaking, alphas associated with low VTR quintiles are positive, though they are not statistically significant. Alphas associated with high VTR quintiles are negative, and are economically and statistically significant. The alphas for low VTR quintiles may be associated with firm size, liquidity costs and other characteristics. To resolve those concerns, I disentangle those effects in Fama-MacBeth cross-sectional regressions in Section V.C.

[Place Figure 8 about here]

In addition, the economic and statistical significance of the negative relation is not limited to the top and the bottom portfolio. The last column of Table IX Panel A reports return difference of a long-short portfolio that longs an equal-weighted portfolio of quintile 4 and quintile 5 and shorts an equal-weighted portfolio of quintile 1 and quintile 2. Regardless of the risk-adjusted benchmark used, the average return and risk-adjusted alphas are economically and statistically significant. The FF3+MOM alpha is -31.5 basis points per month (-3.78% per annum) with a t-statistic of -2.807.

Besides the return difference results for portfolios sorted on VTR, I also report portfolio sorts based on $VLTR$ and $VRTR$ in Table IX Panel B and Panel C, respectively. Panel B reports the return difference and risk-adjusted alphas for quintile portfolios sorted on the left-tail risk measure of volatility, $VLTR$. The last two columns in Panel B reports the High-Low portfolio as well as $(Q4 + Q5) - (Q1 + Q2)$ portfolio results, the definition of which are quite similar to Panel A. Panel C reports return difference and risk-adjusted alphas for quintile portfolios sorted on the the right-tail risk measure of volatility, $VRTR$. Consistent with the strong negative relation between VTR and future cross-sectional stock returns reported in Panel A, both measures also generate impressive negative relations. This suggests that volatility tail risk as a whole has same asset pricing implications. The High-Low portfolio on $VLTR$ generates a monthly four-factor (FF3+MOM) alpha of -34.5 basis points (-4.14% per annum) with a t-statistic of -2.787. Panel C shows that the High-Low portfolio on $VRTR$ yields a monthly four-factor alpha of -28.2 basis points (-3.38% per annum) with a t-statistic equaling to -1.7.

In Figure 9, I examine the profitability of a trading strategy that replicates the Low-High portfolio (reverse the High-Low portfolio in Table IX Panel A) formed on the basis of VTR. As a comparison with other benchmarks, I also compute the cumulative return series for the excess market return, small-minus-big (SMB) and high-minus-low (HML) portfolios (See Fama and French (1993)), as well as momentum (MOM) portfolio (See Carhart (1997)). The VTR-sorted Low-High portfolio and the market portfolio straightly beat the SMB, HML and MOM portfolios over the sample period from January 2004 to December 2014. In contrast, the Low-High portfolio of VTR generates a holding-period return of 70% which is comparable to the contemporaneous market excess return of 88.3%. Even though the raw return of Low-High strategy doesn't surpass S&P 500 index, Figure 3 also shows that the VTR-sorted Low-High strategy suffers impressively less drawback than the market portfolio during 2008 financial crisis, which suggests that this strategy can offer competitive risk-adjusted return. The Sharpe ratio for the VTR-sorted Low-High strategy is 0.7 per annum, excelling the 0.48 annual Sharpe ratio generated by the market index, over the sample period.

[Place Figure 9 about here]

In conclusion, I find strong evidence in support of a negative cross-sectional relation between volatility tail risk, measured by VTR, and subsequent stock returns in the cross-section. The volatility tail risk is relevant in determining stock returns in the cross-section, and its effect is not captured by Carhart (1997) four-factor asset pricing model.

B. Performance Persistence

Having established a strong negative relation between VTR and future stock returns, I next examine the duration of this return predictability. Figure 10 shows the raw returns and alphas of the High-Low strategies with progressively longer holding periods from the observation of VTR signal to portfolio-rebalancing. For example, the VTR High-Low strategy with a 3-month lag means sorting firms into quintile portfolios 3-month prior to the realized return window. Then, I use the monthly time-series of those raw returns to compute alphas (CAPM alpha, FF3 alpha and FF3+MOM alpha). Figure 10 repeats this process with lags from 1- to 4-month.

[Place Figure 10 about here]

The left graph of Figure 10 shows that the return predictability associated with VTR exists for at least 3 to 4 months, where the surrounding error bars represent 95% confidence interval of the corresponding alpha estimation. Even though the 3-month-lag alphas are not statistically significant, we observe a reverse pattern for the 4-month-lag alphas. Not surprisingly, the 1-month-lag alphas are the most significant one from the perspective of both economics and statistics.

The right graph of Figure 10 shows the cumulative alphas from the left graph. We don't observe a reverse trend in cumulative return series for at least 4-month after portfolio formation. This suggests that the volatility tail risk is an important determinant of expected cross-sectional stock returns rather than a mispricing story. The cumulative 4-month risk-adjusted alphas range from -1.25% to -1.41%.

C. Fama-MacBeth Regressions

To further assess the negative relation between the volatility tail-risk measure, VTR, and the cross-section of future stock returns, I conduct various Fama-MacBeth (Fama and MacBeth (1973)) cross-sectional regressions with a battery of control variables. For each month t, I compute the volatility tail-risk measure VTR_t^i for each stock i and estimate the following cross-sectional regressions:

$$r_{t+1}^i = \alpha + \beta VTR_t^i + \gamma' X_t^i + \epsilon_{t+1}^i, \tag{21}$$

where r^i_{t+1} (in percentage) is the stock return (including dividends) of firm i for month $t+1$, and X^i_t represents a vector of characteristics and controls of firm i observed at the end of month t.

[Place Table X about here]

Table X reports the time-series average of the cross-sectional coefficients for the six model estimated. The Newey and West (1987) adjusted t-statistics are reported in square brackets. The first column displays results of regressing monthly return on lagged VTR without any control. The coefficient associated with VTR is -0.0168 with a Newey-West t-statistic of -5.66. This confirms the negative relation found in the portfolio-sorting results, Table IX.

The 5th column reports results of the cross-sectional regression after adding a battery of firm characteristics and controls. Specifically, I control for the equity return jump measure (ERJM), volatility risk premium (VRP), the log of firm size (Size) and the log book-to-market ratio (LBM) as in Fama and French (1993), short-term reversal (Reversal) as in Jegadeesh (1990), momentum return (Momentum) as in Jegadeesh and Titman (1993), maximum monthly return (MaxRet) as in Bali et al. (2011), historical skewness (HSkew), historical kurtosis (HKurt), and Amihud illiquidity measure (Amihud) as in Amihud (2002). The magnitude of the coefficient associated with VTR reduces to -0.089 with a Newey-West t-statistic of -2.57. The stock return kurtosis (HKurt) is also statistically significant at 1% level. However, surprisingly, the coefficient associated with Size is not significant, which suggests potential missing variable concerns.

In the last column, besides the firm characteristics added in Model 5, I also include a set of option-related characteristics to alleviate missing variable issues and guarantee that the volatility tail risk effect is not absorbed by any previously documented factors: average option quote spread of at-the-money options (OptSpread), average implied volatility of at-the-money calls (ImpVol), the volatility skew (OTMSkew) as in Xing et al. (2010), and the option-to-stock volume (O/S) as in Johnson and So (2012). The OptSpread is used to control for liquidity in the option market. The OTMSkew as analyzed by Xing et al. (2010) is associated with stochastic volatility and jumps in stock returns. First of all, the coefficient associated with VTR is still economically and statistically significant after controlling for a battery of characteristics, equaling to -0.0116 with a Newey-West t-statistic of -2.77 (significant at 1% level). The magnitude becomes smaller possibly due to dilutions by some cross-sectional patterns found in Table II. Considering the 10% unconditional standard deviation of VTR in the sample, a two-standard-deviation increase in VTR will lead to a 2.32% drop in expected annual return. It can also be observed that variables such as Size, ImpVol and OTMSkew still play a significant role in the cross-section over the sample period, while characteristics such as LBM, Reversal, Momentum, MaxRet do not show up to be important. The insignificant coefficient associated with O/S is consistent with what Johnson and So (2012) finds in their paper: the return predictability of O/S seems to be short-lived.

As a summary, Table X demonstrates that the economic and statistical significance of the negative volatility tail risk effect, measured by VTR, in the cross-section of expected stock returns is robust to the inclusion of various control variables. The estimated negative relation between VTR and future stock returns in the cross-section is consistent with evidence in Table IX. What's more, Figure 10 rules out the possibility of mispricing: negative High-Low VTR portfolio return lasts for at least a quarter, and shows no sign of reverting back. In the next section, I am going to explore the driving force of this negative relation: is it a systematic priced factor or merely an idiosyncratic anomaly.

D. VTR Decomposition

In this part, I investigate the critical debate that whether VTR is systematically priced in the cross-section. To achieve this purpose, I use SPY VTR as proxy for systematic volatility tail risk measure. Consequently, I decompose stock VTR by projecting onto the span of SPY VTR and constant. The beta component of SPY VTR is classified as systematic VTR, or $sVTR$. The rest part is classified as idiosyncratic VTR, or $iVTR$.

[Place Table XI about here]

In table XI, I report the stock return predictability test using decomposed VTR. Several conclusions can be made: (1) volatility tail risk is *negatively* priced in the cross-section of stock returns. (2) The idiosyncratic VTR component has opposite effect on future stock returns compared to systematic VTR. (3) The economic impact of systematic VTR on future cross-section of stock returns is five times large than that of idiosyncratic VTR.

Our results on VTR decompositions are consistent with the structural estimation on the price of risk of volatility jumps by Eraker (2004). This can be explained from a risk-compensation story:

VTR and stock return is negatively correlated. In SPY time-series, the time-series correlation between SPX return and VTR is -0.3. Consequently, an asset that pays off VTR while stock return is low is essentially a hedging asset to the economy, which should pay off with negative price of risk. This argument has the same logic as the negative volatility risk premium.

In addition, this negative price of risk is also consistent with the negative idiosyncratic volatility relation. Recently, Stambaugh, Yu, and Yuan (2015) investigates the idiosyncratic volatility (IVOL) puzzle from an arbitrage asymmetry perspective. In financial markets, buying is usually easier than shorting for many equity investors. The IVOL-return relation is negative among overpriced stocks but positive among underpriced stocks. Consistent with arbitrage asymmetry theory, the negative relation is stronger, especially for stocks less easily shorted. They also find evidence that high investor sentiment weakens positive relation among underpriced stocks and strengthens the negative relation among overpriced stocks. Meanwhile, we also show that our VTR measure is not only strongly associated with idiosyncratic risk contemporaneously, but also positively predicts idiosyncratic risk in the next period. Consequently, this negative relation arises.

E. Alternative Volatility Tail Risk Measures and Stock Returns

Having established alternative volatility tail risk measures in Section IV, we want to investigate whether the negative relation is robust to alternative measures or just special to VTR itself.

[Place Table XII about here]

At the end of each week, stocks are sorted into quintile portfolios based on IVKurt (λ^{LT} or λ^{RT}) with the lowest located in the 1st quintile and the highest located in the 5th quintile. Table XII Panel A reports portfolio-sorting results based on IVKurt. Table XII Panel B reports portfolio-sorting results based on λ^{LT} and Panel C displays results of λ^{RT}. In the subsequent analysis, I will mainly focus on the IVKurt measure. Even though the raw portfolio return for the first quintile of IVKurt is a little lower than the 2nd quintile, there still exists a downward trend in raw returns from low quintile portfolio to high quintile portfolio. The High-Low strategy of IVKurt that buys stocks in the 5th quintile and sells stocks in the 1st quintile generates an average monthly return of -30.8 basis points (-3.7% per annum) with a t-statistic of -2.347. The Carhart four-factor alpha for the High-Low portfolio is -26.2 basis points (-3.15% per annum) with a t-statistic of

-1.756. Furthermore, the long-short strategy that longs an equal-weighted portfolio in quintile 4 and 5 and shorts an equal-weighted portfolio in quintile 1 and 2 generates an annual four-factor alpha of -3.55% with a Newey-West t-statistic of -2.815.

[Place Table XIII about here]

To further assess the robustness of this negative relation, I conduct Fama and MacBeth (1973) cross-sectional regressions by regressing monthly stock returns (in percentage) on IV kurtosis (IVKurt), volatility-of-volatility (VoV), IVSkew and a battery of other control variables described in Section II.C. The volatility-of-volatility (VoV) variable is constructed as Baltussen et al. (2014). Section VI.A provides a thorough examination of the volatility-of-volatility risk. Table XIII reports the time-series average of cross-sectional coefficients under three specifications. Table XIII Model 1 shows results of regressing monthly returns on IVKurt and constant. The coefficient associated with IVKurt equals to -0.0002 with a Newey-West t-statistic of -4.03. This provides support to the negative relation found in Table XII. Model 3 displays estimates after controlling for firm characteristics as well as VoV and IVSkew. The coefficient associated with IVKurt reduces in magnitude to -0.0001 with a Newey-West t-statistic of -2.143 (statistically significant at 5% level). A close examination of coefficients of other controls reveals that the factors that play important roles coincide with those reported in Table X: for example, coefficients associated with Size, ImpVol and OTMSkew are still economically and statistically significant. This indicates that these cross-sectional patterns are quite robust over my sample period from January 2004 to December 2011.

In summary, the evidence in Table XII and Table XIII supports the validity of my volatility tail risk measure, VTR. It also confirms the robustness of the negative relation between volatility tail risk and future cross-sectional stock returns documented in Subsection V.C. The Fama and MacBeth (1973) results in Table XIII also shed light on the interactions between between IVKurt and volatility-of-volatility (VoV), and indicate that volatility skewness (IVSkew) doesn't seem to be an important stock return determinant in the cross-section.

VI. Robustness Tests

The volatility tail risk measure, VTR, is closely related to a strand of literature that studies volatility-related characteristics and their impact on the cross-section of stock returns. In particular, Ang et al. (2006) and Ang et al. (2009) show that idiosyncratic volatility carries a puzzling feature that high idiosyncratic volatility stocks predict low expected stock returns. This puzzling feature is pervasive among other international markets. In addition, Huang and Shaliastovich (2014) argues that the volatility-of-volatility risk is a priced factor and bears a negative price of risk. In contrary, Baltussen et al. (2014) empirically studies the volatility-of-volatility risk and shows that the volatility-of-volatility risk seems to be an idiosyncratic feature. Despite of these inconsistencies, both of them show in their paper that volatility-of-volatility risk affects the cross-section of stock returns. Finally, from analysis in previous sections, I would like to know how VTR interacts with firm characteristics, e.g. firm size. In addition, since I construct this measure using option data, it is important to address the question that how option characteristics affect the negative cross-sectional predictability of VTR.

A. Volatility-of-Volatility Effect

The topic of this paper is closely related to the volatility-of-volatility concept in Baltussen et al. (2014) and Huang and Shaliastovich (2014), both in economic and statistical sense. Albeit from different angle, both authors show that volatility-of-volatility is a crucial factor that determines stock returns in the cross-section. They, however, differ on a central issue that whether volatility-of-volatility risk should be a systematically priced factor. Nevertheless, empirical evidence suggests that it might be important to rule out the effect of volatility-of-volatility by controlling for this feature.

Recent finance literature has demonstrated that variance risk is closely related to the tail risk of underlying stock price. Particularly, one strand of literature draws focus on disentangling tail risk premium from variance risk premium. For example, Bollerslev, Todorov, and Xu (2015), relying on a new model-free estimation procedure, shows that much of the predictability that variance risk premium predicts future stock market return might be attributed to time variation in the part of variance risk premium associated with special compensation demanded by investors for bearing jump risk or tail risk. In macro-finance field, researchers have found that disaster risk is a plausible solution to the equity premium puzzle (e.g. Barro (2006), Gabaix (2012)). All those insights imply that volatility tail risk should be as important as volatility-of-volatility risk.

I formally test the interactions between volatility tail risk and volatility-of-volatility risk (Baltussen et al. (2014)) using the Fama and MacBeth (1973) cross-sectional regressions described below:

$$r^i_{t+1} = \alpha + \beta_1 VTR^i_t + \beta_2 VoV^i_t + \beta_3 IVSkew^i_t + \gamma' X^i_t + \epsilon^i_{t+1}, \tag{22}$$

where r^i_{t+1} (in percentage) is the stock return (including dividends) of firm i for month $t+1$, and X^i_t represents a vector of characteristics and controls of firm i observed at the end of month t. $IVSkew^i_t$ is the monthly realized skewness of volatility defined in Equation 14.

The VoV, or volatility-of-volatility, is built as Baltussen et al. (2014). The volatility-of-volatility of stock i for month t is constructed as follows:

$$VoV^i_t = \frac{1}{\overline{\sigma}^{IV,i}_t}\sqrt{\frac{1}{N_t}\sum_{j=1}^{N_t}(\sigma^{IV,i}_{j,t} - \overline{\sigma}^{IV,i}_t)^2}, \tag{23}$$

where $\overline{\sigma}^{IV,i}_t = \frac{1}{N_t}\sum_{j=1}^{N_t}\sigma^{IV,i}_{j,t}$ is the average of daily IV over month t, and N_t is the number of daily observations over month t.

[Place Table XIV about here]

Table XIV Panel A reports the time-series average of coefficients in Equation 22. Model 1 to 3 displays estimated coefficients associated with VTR, VoV and IVSkew, respectively. Under an univariate specification, we find a negative relation between VoV and future stock returns in the cross-section, which is consistent with what Baltussen et al. (2014) reveals in their paper. IVSkew, on the other hand, doesn't seem to be a determinant of future stock returns in the cross-section, at least in-sample. The Fama and MacBeth (1973) results for multivariate regression with firm characteristics are reported in the last column under tab "Model 5". The coefficient associated with VTR is -0.012 with a Newey-West t-statistic of -2.71 (statistically significant at 1% level). To my surprise, the VoV effect gets completely absorbed by VTR and other firm characteristics. Those prominent cross-sectional features reported in Table X, such as Size, ImpVol and OTMSkew, continue to make an impact in Model 5. The bottom line, to be as conservative as possible, is that the volatility tail risk in itself is an important determinant of expected stock returns in the cross-section and doesn't get silenced by the volatility-of-volatility effect.

To shed deep light on the inter-connection between vol-of-vol and VTR, I perform a double-sorting test on VTR and vol-of-vol. At the end of each month, stocks are first sorted into quintile portfolios by vol-of-vol, and further sorted into quintile portfolios based on VTR within each vol-of-vol group. The double-sorting outcome is reported in Table XIV Panel B. Panel B-1 gives results on excess return, and Panel B-2 gives shows results on Carhart (1997) four-factor alpha. I show that even after controlling for vol-of-vol effect, the negative abnormal return still exists for High-Low VTR portfolio. Admittedly, the performance of High-Low VTR portfolio for vol-of-vol Q2 and Q3 are not so satisfactory. In fact, we see that though the low VTR portfolio exhibits relatively low returns. The Q2 and Q3 display higher returns. In fact, the long-short strategy that uses Q2 instead of Q1 generates an economically and statistically significant abnormal return. I would accrue this not-so-satisfactory evidence to micro-structure issues inherent in the options market. Albeit I am very careful when constructing VTR, I still cannot fully rule out the impact of micro-structure issues on my results. As a conclusion, I argue that the vol-of-vol effect documented by Baltussen et al. (2014) and Huang and Shaliastovich (2014) cannot explain the negative relation between VTR on the cross-section of stock returns.

B. *VTR and Stock Volatility*

One of the most prominent strand literature in volatility-related asset pricing is the well-known topic on stock volatility and its impact on the cross-section of stock returns (e.g. Ang et al. (2006), and Ang et al. (2009)). The ground-breaking paper by Ang et al. (2006) shows two main results: (1) the first result is that market volatility is a priced risk factor in the cross-section and bears negative price of risk, which is consistent with risk-based theories; (2) the second result is that the idiosyncratic volatility, after controlling for Fama and French (1993) three factors, negatively impact the cross-section of stock returns, and cannot be explained by exposure to aggregate volatility risk or other asset pricing models. Built on this insight, Ang et al. (2009) further demonstrate that this "idiosyncratic volatility puzzle" is pervasive among other international markets. They also rule out explanations based on trading frictions, information dissemination, and higher moments.

In this subsection, I intend to decompose the interaction between VTR and stock volatility effects, i.e. total volatility and idiosyncratic volatility. Due to the close relation between volatility tail risk and stock return volatility (total volatility, and idiosyncratic volatility), it is nontrivial to investigate and disentangle the validity of the VTR effect. In this section, I explore the interconnections using two approaches: (1) the first approach is to explore portfolio returns from double-sorting on VTR and stock volatility (either total volatility or idiosyncratic volatility). (2) The second approach is more straight-forward. I conduct cross-sectional regressions by controlling for stock volatility. The outcomes of these two approaches are reported in XV Panel A and Panel B, respectively.

The definitions of total volatility (tVol) and idiosyncratic volatility (iVol) follow directly from Ang et al. (2006). *tVol*, short for total volatility, is estimated as the volatility of stock's daily returns over a certain horizon, which is set to a calendar month under the circumstance of this paper. *iVol*, short for idiosyncratic volatility, is defined relative to the Fama and French (1993) three-factor factor model. Mathematically, iVol is computed as the standard deviation of the residuals of the Fama and French (1993) three-factor regression. To disentangle VTR from tVol (or iVol), I implement the conditional double-sorting approach at the end of each calendar month. Stocks are first sorted into quintile portfolios based on tVol (or iVol), then further sorted into quintile portfolios based on VTR within each volatility group. Portfolios are held for the subsequent month and are rebalanced every month.

[Place Table XV about here]

In Table XV Panel A, I report the double-sorting results on tVol and iVol, respectively. The Carhart (1997) four-factor alphas are estimated for all portfolios with the corresponding Newey-West adjusted standard errors reported in the square brackets. The last column reports the performance of an equal-weighted long-short investment strategy that buys stocks in the highest VTR quintile and sells stocks in the lowest VTR quintile within each tVol (or iVol) quintile. The double-sorting abnormal return for VTR-sorted portfolios exhibits similar pattern for both total volatility and idiosyncratic volatility: the negative abnormal alphas are concentrated in stocks with high stock return volatility (both tVol and iVol). The High-Low VTR portfolio of the highest tVol quintile generates an abnormal return of -0.7% per month (-7.3% per annum), which is also economically and statistically significant. This pattern shows that my VTR measure captures additional downside risk information that is not captured by stock return volatility. After controlling for idiosyncratic volatility (iVol), the bottom section of Table XV Panel A shows that the statistically significant abnormal return also exists for High-Low VTR portfolio with high iVol. Overall, these evidence shows that the downside risk information captured by VTR is not fully collided with what is already captured in stock return volatility, either the market component or the idiosyncratic component.

In terms of why negative abnormal returns only exists in high tVol (and iVol) portfolios, there are two possible explanations: (1) stocks with low volatility are less likely to have volatility jumps in the volatility process, therefore, VTR might bear measurement errors; (2) second, stocks with low volatility are less likely to have exposure to the downside risk induced by volatility fat-tail distribution. Since implied volatility is market's expectation about future stock volatility, variations in implied volatility will reflect information fluctuations in the fundamentals and changes in investors' expectations. This is related to economic questions on how information incorporates into asset prices and whether option market has superior information about underlying asset prices.

Take an additional step forward, I also test the first-order effect of stock return volatility on VTR in Fama and MacBeth (1973) cross-sectional regression by controlling for tVol and iVol. In XV Panel B, empirical results on the joint cross-sectional regressions are provided. Not surprisingly, the magnitude of VTR on the cross-section of stock returns seems to vary little across a variety of specifications. Neither total volatility nor idiosyncratic volatility substantially affects the magnitude and the predicting sign of VTR. This evidence serves as additional support that volatility tail risk is not a mere proxy of market volatility or idiosyncratic stock volatility puzzle documented by Ang et al. (2006), and captures additional downside risk about the fundamentals that is not captured by stock return volatility only.

C. VTR and Firm Characteristics

In this subsection, I further explore the interaction between VTR and other firm characteristics using double-sorting strategy. Among all firm characteristics, firm size and option related variables are of special interest to me. Existing literature studying cross-section of stock returns often show that return anomaly are most pronounced in small-cap firms. In aforementioned sections, I have shown that the downside risk captured by VTR is unlikely to be systematic risk from risk-compensation perspective. Due to the fact that implied volatility actually reflects investors' expectations, I therefore argue that the negative return predictability could be very well driven by an information story: option investors are informative about underlying stock prices, and the VTR is associated with information asymmetry in stock prices. Under this hypothesis, I would argue that information are more likely to be revealed for stocks with high option trading volume and high degree of information asymmetry, albeit the relation might be linear.

The unconditional correlation matrix between VTR and other firm characteristics is reported in Table VIII Panel A. For other firm characteristics displayed in Table VIII Panel B, I don't put special focus on them either because their low correlation with VTR measure or not quite relevant to the economic story behind. In the text below, I first explore the interaction between VTR and firm size, then try to link the negative predictability to economic story from an information perspective. Consistent with microstructure literature, I use option quoted spread as a measure of information asymmetry, and option trading volume as a measure of option liquidity.

The relation between VTR and firm size is investigated using double-sorting strategy. Specifically, by the end of each month, stocks are first sorted into quintile portfolios by firm size, and then sorted into quintile portfolios by VTR within each size group. Consequently, 25 portfolios are formed based on these two criteria. Table XVI Panel A reports average raw returns of each portfolio as well as High-Low portfolio of VTR conditional on Size. Panel B reports the Carhart (1997) four-factor alpha of each portfolio. This double-sorting strategy allows us to evaluate volatility tail risk effect conditional on different size levels. The results for the High-Low portfolio of VTR conditional on Size are reported in the last column of each panel.

[Place Table XVI about here]

Not surprisingly, the negative volatility tail risk effect is most prominent among small-cap firms. For example, the monthly Carhart (1997) four factor alpha of High-Low VTR portfolio for Size quintile 1 is -1.1% (that is approximately 13% per annum), with a statistically significant t-statistic at 1% level. In contrast, stocks beyond the lowest size quintile do not show significant volatility tail risk effect. This result is consistent with the aforementioned idiosyncratic volatility results: as showed in Subsection VI.B, stock volatility is usually high for small-cap stocks, and the negative volatility tail risk effect is also stronger for stocks with high volatility stocks. The findings are also consistent with many cross-sectional stock return studies, which find cross-sectional predictable patterns are generally stronger for small stocks[4].

VII. Conclusions

Finance literature has shown in various ways that jump in volatility is a crucial feature in dientangling complex asset pricing phenomenon: first of all, jumps in volatility allow for rapid increase in stock volatility, while other features cannot address this issue. Furthermore, jumps in volatility allow persistent shocks to asset returns with large magnitude. In this paper, I develop a novel non-parametric volatility tail risk measure using a sample of high-frequency intraday option quotes and trades from January 2004 to December 2014. The volatility tail risk measure is conditional at monthly frequency. First and foremost, the advantage of using non-parametric measure, in contrast to parametric measure (i.e. complex structural models), is that non-parametric approach is immune to model misspecifications. Frankly speaking, unlike experimental science, it is hard to testify the validity of a model. Furthermore, structural models with both jumps in stock return and volatility, as well as stochastic volatility process (multiple hidden factors), make the accurate estimation of parameters a tough task even with MH algorithm and Gibbs sampling.

To validate that VTR indeed measures jump components in IV process, I use a non-parametric approach proposed by Lee and Mykland (2007) to identify jumps in the IV process. Built on the identified jumps from IV process, I develop three extended IV jump measures: IVJI, IVJS and IVSJS. IVJI stands for IV jump intensity. IVJS stands for IV jump size and IVSJS stands for IV scaled jump size. I show that VTR is robustly related to all three IV jump measures, particularly for IVSJS. Furthermore, VTR is also one of the most effective predictor of future IV jumps in the cross-section.

The volatility tail risk is closely linked to future economic conditions, both contemporaneously and subsequently. I find strong evidence that the constructed volatility risk measure, VTR, is positively correlated with stock return jump risk, volatility risk, implied volatility, idiosyncratic volatility, firm size and liquidity measure (stock liquidity and option liquidity), contemporaneously. In particular, firm size (as well Amihud illiquidity measure and option liquidity measure, option quoted spread), persistently, accounts for a critical fraction of the total cross-sectional variation in

[4]For example, Ang et al. (2006), Xing et al. (2010), Baltussen et al. (2014), Amaya et al. (2015).

VTR. Furthermore, stocks with high VTR tends to bear high uncertainty in the future. The non-parametric volatility tail risk measure forecasts future stock return jump measure, volatility risk premium, idiosyncratic volatility, Amihud liquidity measure, option quoted spread, return skewness and kurtosis with non-trivial economic magnitude and impressive statistical significance.

I find a reliable and significant negative relation between my volatility tail risk measure, VTR, and next month's stock returns in the cross-section. In terms of return magnitude, when sorting stocks into quintile portfolios based on VTR, stocks with the highest VTR underperform stocks with the lowest VTR by 5.23% per annum in raw returns, equivalent to 5.1% per annum on a risk-adjusted basis (Carhart (1997) four-factor alpha). This negative effect is economically substantial, a trading strategy that buys stocks with low VTR and sells with high VTR over the sample period generates a total holding-period return of 70%, which is comparable to the cumulative market excess return of 88%, but with a much higher Sharpe of 0.7 per annum. In comparison, the contemporaneous Sharpe ratio for the market portfolio is merely 0.48.

The negative volatility tail risk effect is robust and has a distinct nature. The negative performance is persistent: the performance of the High-Low VTR-sorted portfolio is persistent for at least 3 to 4 months, ruling out the possibility of mispricing. I provide evidence that the negative volatility tail risk effect in the cross-section survives the inclusion of a battery of well-documented characteristics, such as size, book-to-market, historical skewness (kurtosis), maximum return of previous month, short-term reversal, momentum, Amihud illiquidity, and option-related features. Particularly, I confirm that, albeit related, the volatility tail risk effect is not mitigated by the idiosyncratic volatility anomaly and the volatility-of-volatility effect, which are mostly relevant. Furthermore, I show that the negative volatility tail risk effect is stronger for small-cap, high idiosyncratic volatility, large option spread stocks.

Several possible explanations exist behind this negative volatility risk effect: (1) volatility tail risk bears a negative price of risk and is priced into asset prices, including both stock prices and option prices. We show in the paper that the negative VTR-return relation is driven by systematic component in VTR through a decomposition analysis. This can be explained from a risk-compensation story: VTR and stock return is negatively correlated. In SPX time-series, the time-series correlation between SPX return and VTR is -0.3. Consequently, an asset that pays off VTR while stock return is low is essentially a hedging asset to the economy, which should pay off with negative price of risk. This argument has the same logic as the negative volatility risk premium. (2) Second, Stambaugh et al. (2015) investigates the idiosyncratic volatility (IVOL) puzzle from an arbitrage asymmetry perspective. In financial markets, buying is usually easier than shorting for many equity investors. The IVOL-return relation is negative among overpriced stocks but positive among underpriced stocks. Consistent with arbitrage asymmetry theory, the negative relation is stronger, especially for stocks less easily shorted. They also find evidence that high investor sentiment weakens positive relation among underpriced stocks and strengthens the negative relation among overpriced stocks. Meanwhile, we also show that our VTR measure is not only strongly associated with idiosyncratic risk contemporaneously, but also positively predicts idiosyncratic risk in the next period. Thus, I argue that the VTR can affect the expected stock return through the proposed idiosyncratic risk channel. (3) Third, the negative relation can also be related to uncertainty story. In the paper, we show that VTR predicts future uncertainty measure in stock returns, such as idiosyncratic volatility, stock return jump risk and volatility risk. This evidence is consistent with findings in Glosten, Jagannathan, and Runkle (1993) who finds support for a negative relation between conditional expected monthly return and conditional variance of monthly return in a GARCH-M model.

Appendix A. Option Sample Selection

This appendix gives a detailed description on how I construct the final option sample for implied volatility computation. The high-frequency intraday option quotes data are from Nanex. I apply the following filters to the options data:

1. For stocks:
   - Only include common equity shares that are listed on NYSE, AMEX and NASDAQ.
   - The stock trading volume must be positive.
   - The stock closing price must be higher than \$1.
2. For options:
   - The option trading volume must be positive.
   - Moneyness: $0.95 <= SK/S <= 1.05$, where S is the stock closing price and SK is the strike price of the option.
   - Time to expiration: closest to 30 days.
   - The earliest quote available must be no later than 9:40am. The last quote available must be later than 3:50pm. As we know, option market is not as liquid as stock market, this requirement is to alleviate liquidity concerns arisen from option market.

Furthermore, in order to extract valuable and reasonable implied volatility information from high-frequency option quotes, I rule out observations where option quotes are problematic: (1) Bid > Ask; (2) either Bid or Ask is missing; (3) Bid < \$0.1; (4) Ask is higher than twice stock price; (5) (Ask-Bid)> \$10 or (Ask-Bid)/Bid>0.7 or (Ask-Bid)>Stock Price. I choose ATM option as the benchmark for implied volatility because it has the highest liquidity among all traded options. In fact, in terms of trading volume, the total trading volume of ATM calls and puts accounts for approximately 40% of total daily volume.

Appendix B. Identify Jumps in IV Process

This appendix provide a brief description of the Lee and Mykland (2007)'s nonparametric approach under the settings of this paper. In particular, to simplify notations, the superscript representing any given firm will be suppressed unless necessary. The definition of test statistic $\mathcal{L}(i)$ follows from **Definition 1** in Lee and Mykland (2007):

DEFINITION 1: *The statistic $\mathcal{L}(i)$, which tests at time t_i whether there was a jump from t_{i-1} to t_i, is defined as:*

$$\mathcal{L}(t_i) = \frac{ln\left(\sigma^{IV}(t_i)/\sigma^{IV}(t_{i-1})\right)}{\widehat{\Sigma(t_i)}}, \tag{B1}$$

where the instantaneous volatility $\widehat{\Sigma(t_i)}$ is estimated using realized bipower variations,

$$\widehat{\Sigma(t_i)}^2 = \frac{1}{K-2}\sum_{j=i-K+2}^{i-1} |ln\left(\sigma^{IV}(t_j)/\sigma^{IV}(t_{j-1})\right)||ln\left(\sigma^{IV}(t_{j-1})/\sigma^{IV}(t_{j-2})\right)|. \tag{B2}$$

The choice of window size K is proposed and proved in **Theorem 1** of Lee and Mykland (2007). Lee and Mykland (2007)'s **Theorem 1** suggests the optimal window size K should fall in $(\sqrt{252\times nobs}, 252\times nobs)$, where $nobs$ is the number of observations per day. In the context of this paper, the time interval $\Delta_t = t_i - t_{i-1}$ =1-minute, corresponding to $nobs = 390$ (trading hours). To alleviate microstructure noise, I choose the time-window to be **three-day**.

The process of identifying jumps in IV involve addressing the rejection region when statistic $|\mathcal{L}(i)|$ is too large. The lemma below is modified based on **Lemma 1** in Lee and Mykland (2007):

LEMMA 1: *If conditions for $\mathcal{L}(i)$, K, $\overline{A}_n$, and c are defined as in Lee and Mykland (2007)'s Theorem 1, then as $\Delta_t \to 0$,*

$$\frac{max_{i\in\overline{A}_n}|\mathcal{L}(i)| - C_n}{S_n} \to \xi, \tag{B3}$$

where ξ has a cumulative distribution function $P(\xi \le x) = exp(-e^x)$,

$$C_n = \frac{\sqrt{2ln(n)}}{c} - \frac{ln(\pi)+ln(ln(n))}{2c\sqrt{2ln(n)}} \quad and \quad S_n = \frac{1}{c\sqrt{2ln(n)}}, \tag{B4}$$

where n is the number of observations per day and $c = \sqrt{2}/\sqrt{\pi} \approx 0.7979$.

In short, the main idea in selecting a rejection region is that if the observed test statistics are not even within the usual region of maximums, it is unlikely that the realized return is from the continuous part of the jump diffusion model. To apply this result for selecting a rejection region, for instance in my application, I set the significance level to 1%. Then the threshold for $\frac{|\mathcal{L}(i)| - C_n}{S_n}$ is ξ^*, such that $P(\xi \leq \xi^*) = exp(-e^{\xi^*}) = 0.99$. Equivalently, $\xi^* = -ln(-ln(0.99)) = 4.6$. Therefore, if $\frac{|\mathcal{L}(i)| - C_n}{S_n} >= 4.6$, then I reject the hypothesis of no jump at t_i.

[Place Figure 11 about here]

Figure 11 is cited from Figure 1 in Lee and Mykland (2007). This graph illustrates the intuition that how this jump detection test distinguishes the jump arrivals. The jump detection statistic $\mathcal{L}$ is formulated by taking the ratio of the last return in a window to the *instantaneous volatility*, estimated by bipower variation using the returns in the same window.

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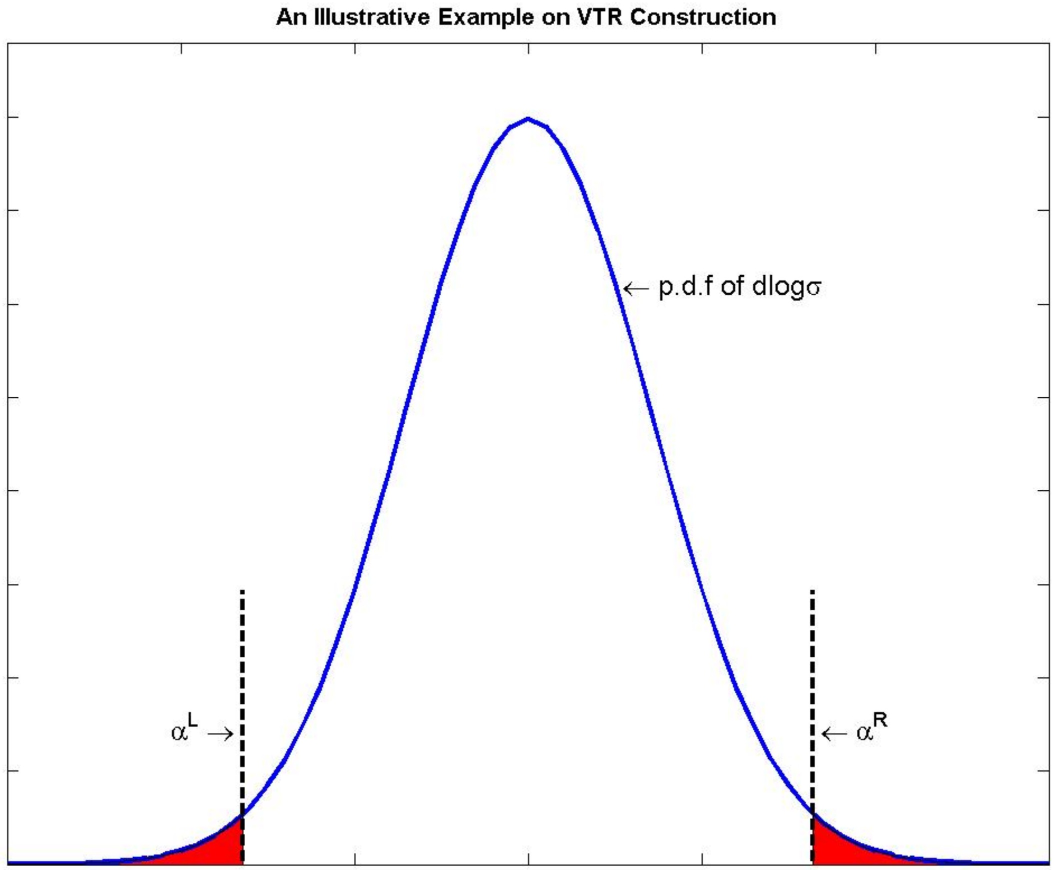

Figure 1. An Illustrative Example on VTR Construction. This figure provides an illustrative example on how I define the tail variation in the intraday distribution of $dlog(\sigma^{IV})$. α^L (α^R) is the left (right) threshold chosen to construction left-(right-)tail variation in implied volatility.

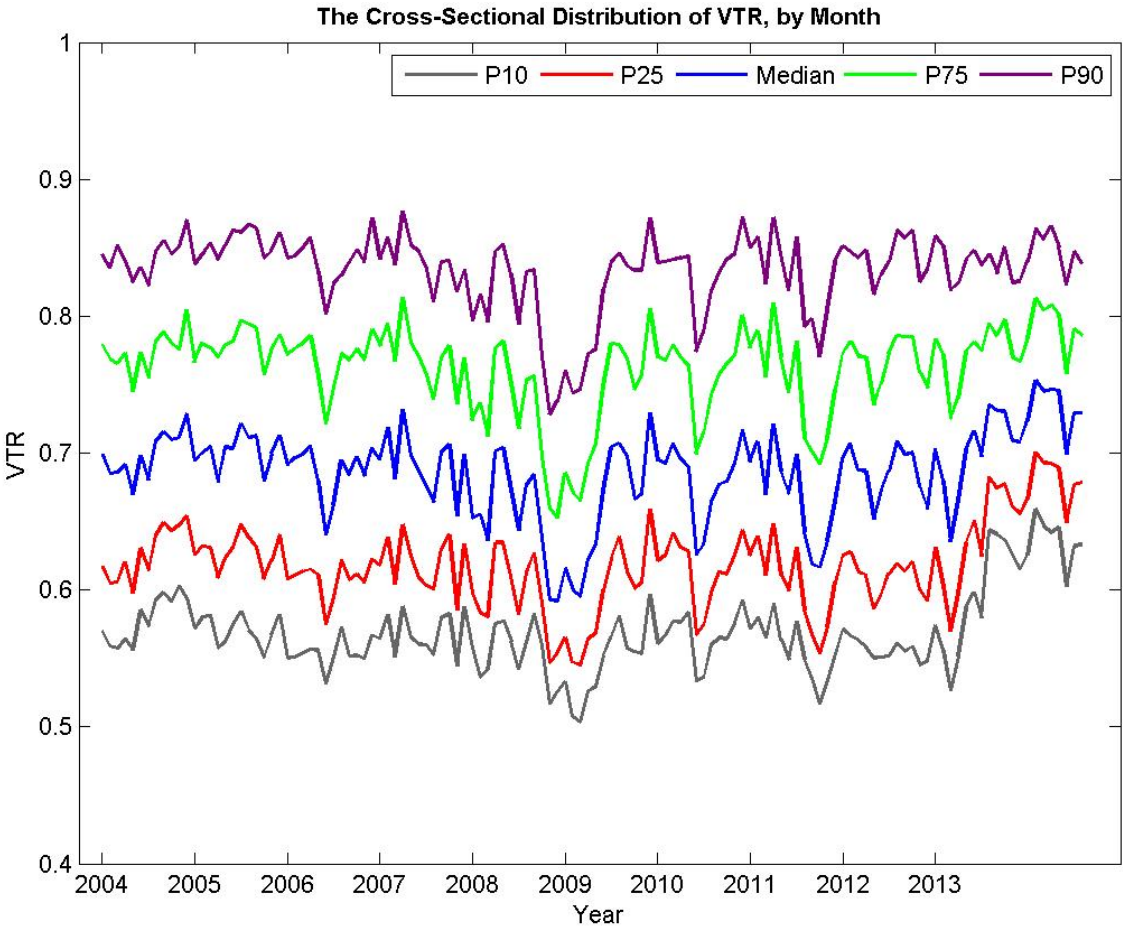

Figure 2. The Cross-Sectional Distribution of VTR. This figure displays the distribution percentiles of VTR for the cross-section of stocks by year-month. VTR is the monthly tail risk measure of IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. The sample consists of 156,509 firm-month observations over the time period January 2004 to December 2014.

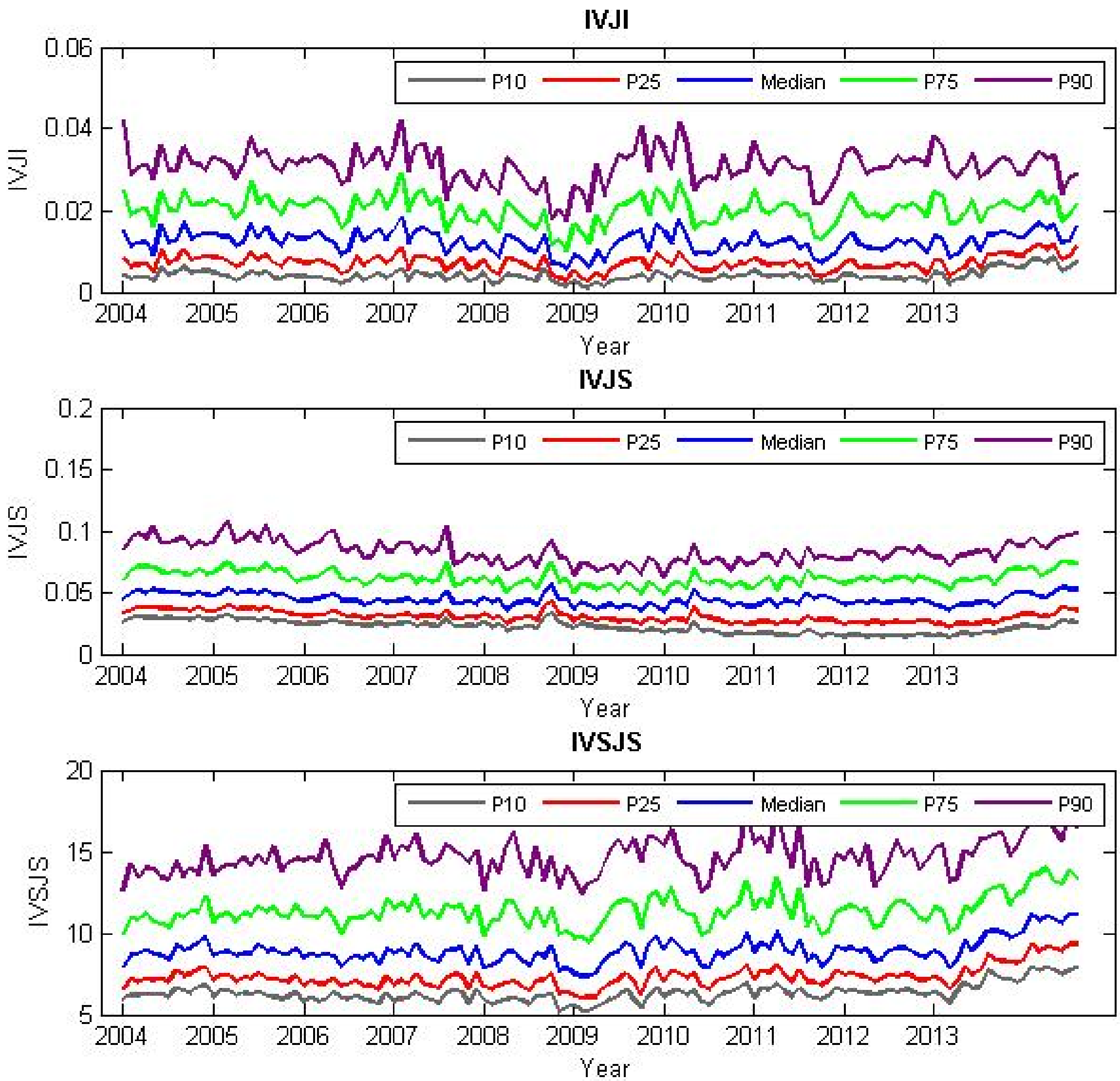

Figure 3. The Cross-Sectional Distribution of Lee and Mykland (2007) IV Jump Measures (IVJI/IVJS/IVSJS). This figure displays the cross-sectional distributions of IV jump measured constructed using Lee and Mykland (2007) non-parametric identification strategy. IVJI represents IV jump intensity. IVJS represents IV jump size. IVSJS represents IV scaled jump size. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. The sample consists of 156,509 firm-month observations over the time period January 2004 to December 2014.

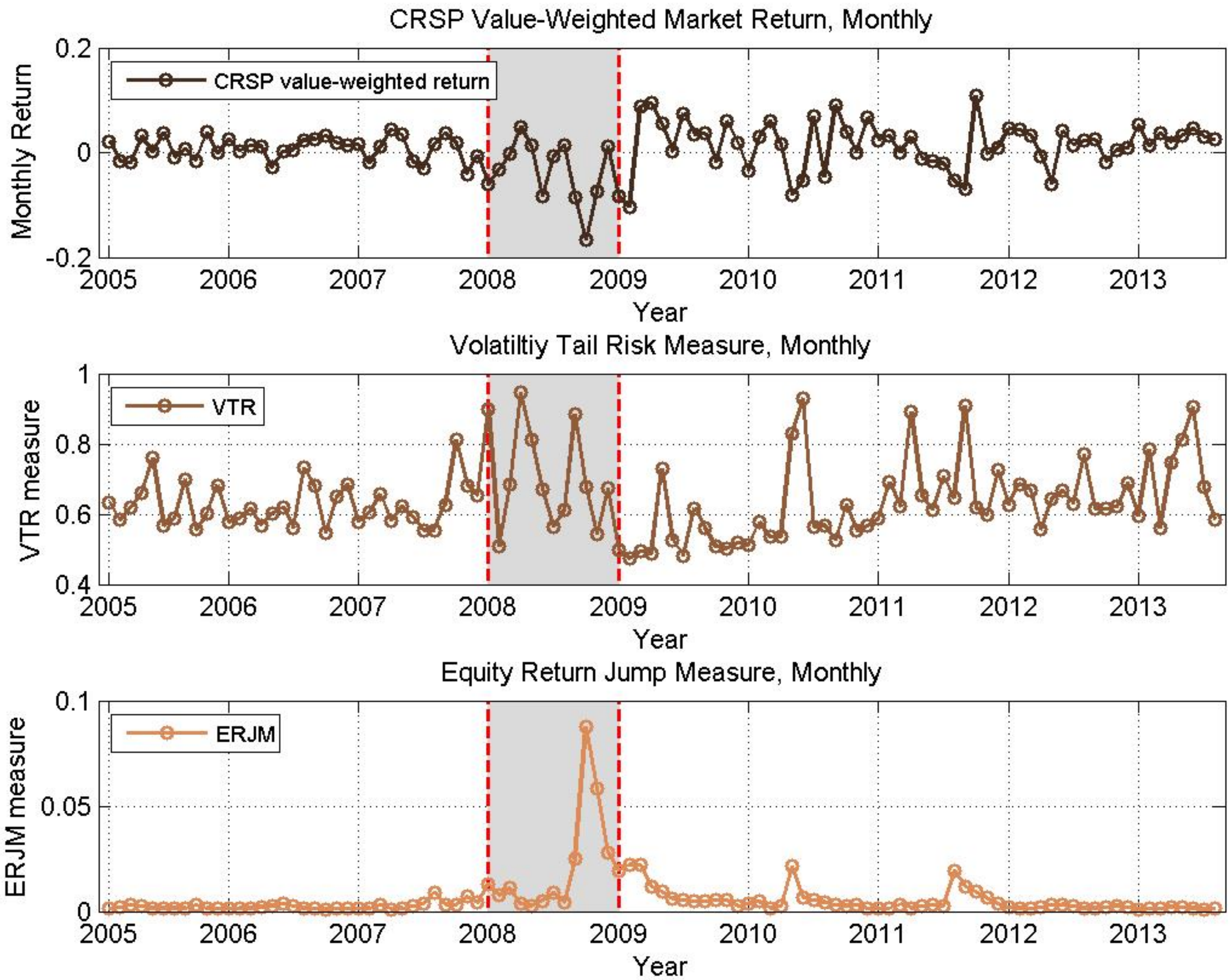

Figure 4. The Time-Series of SPY Stock Return, VTR and $ERJM$. This figure displays the time-series of SPY stock return, VTR and $ERJM$. The VTR is the constructed volatility tail risk measure. $ERJM$ is the equity return jump measure constructed based on Bollersleve and Todorov (2011). The sample contains monthly observations from January 2005 to December 2015.

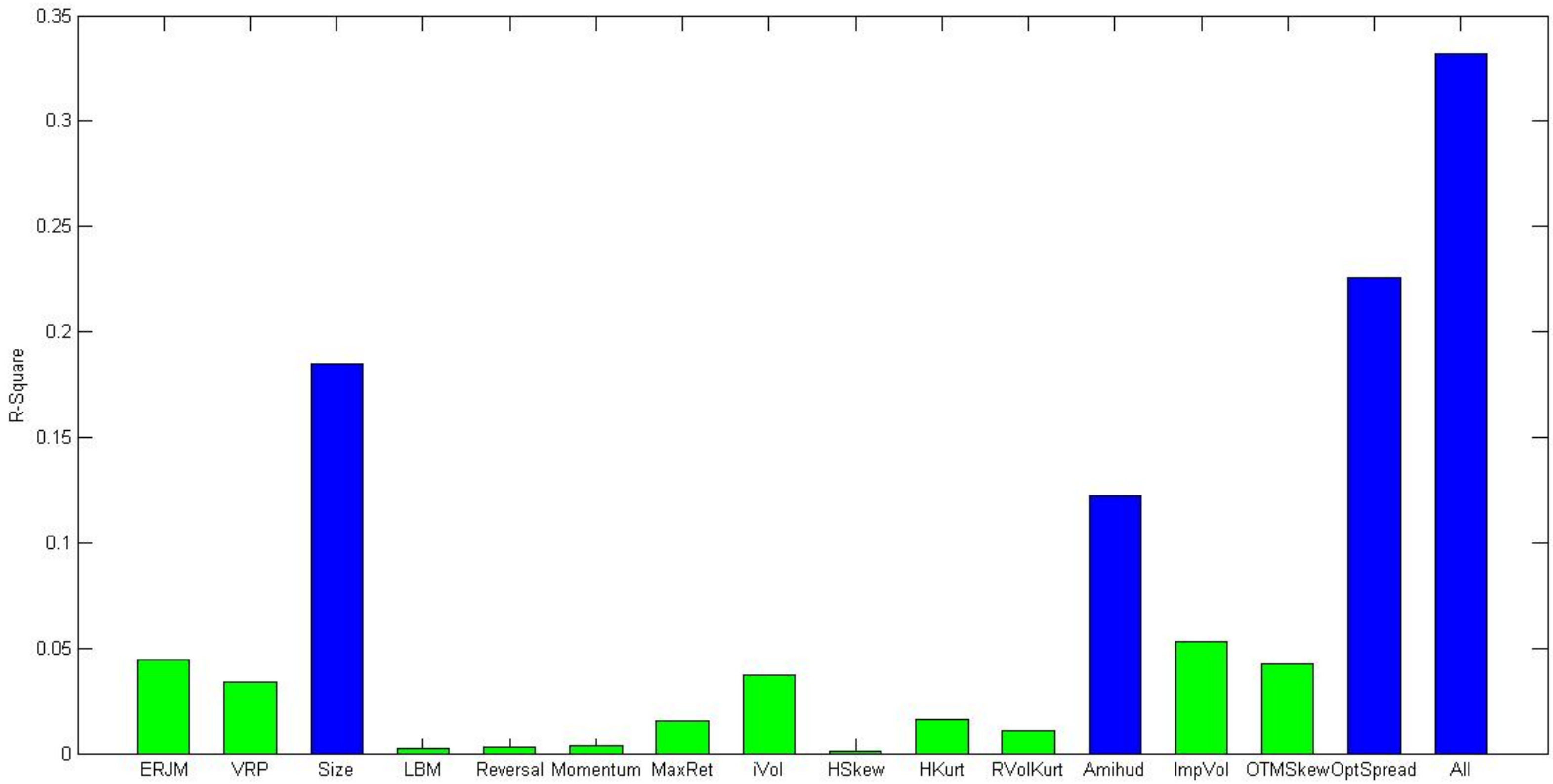

Figure 5. Marginal R-Squares. This figure reports the marginal R-Squares of univariate regressions of VTR on firm characteristics. Specifically, the *Blue* bars represent greater than 10% R-Squares. The sample period is from January 2004 to December 2014.

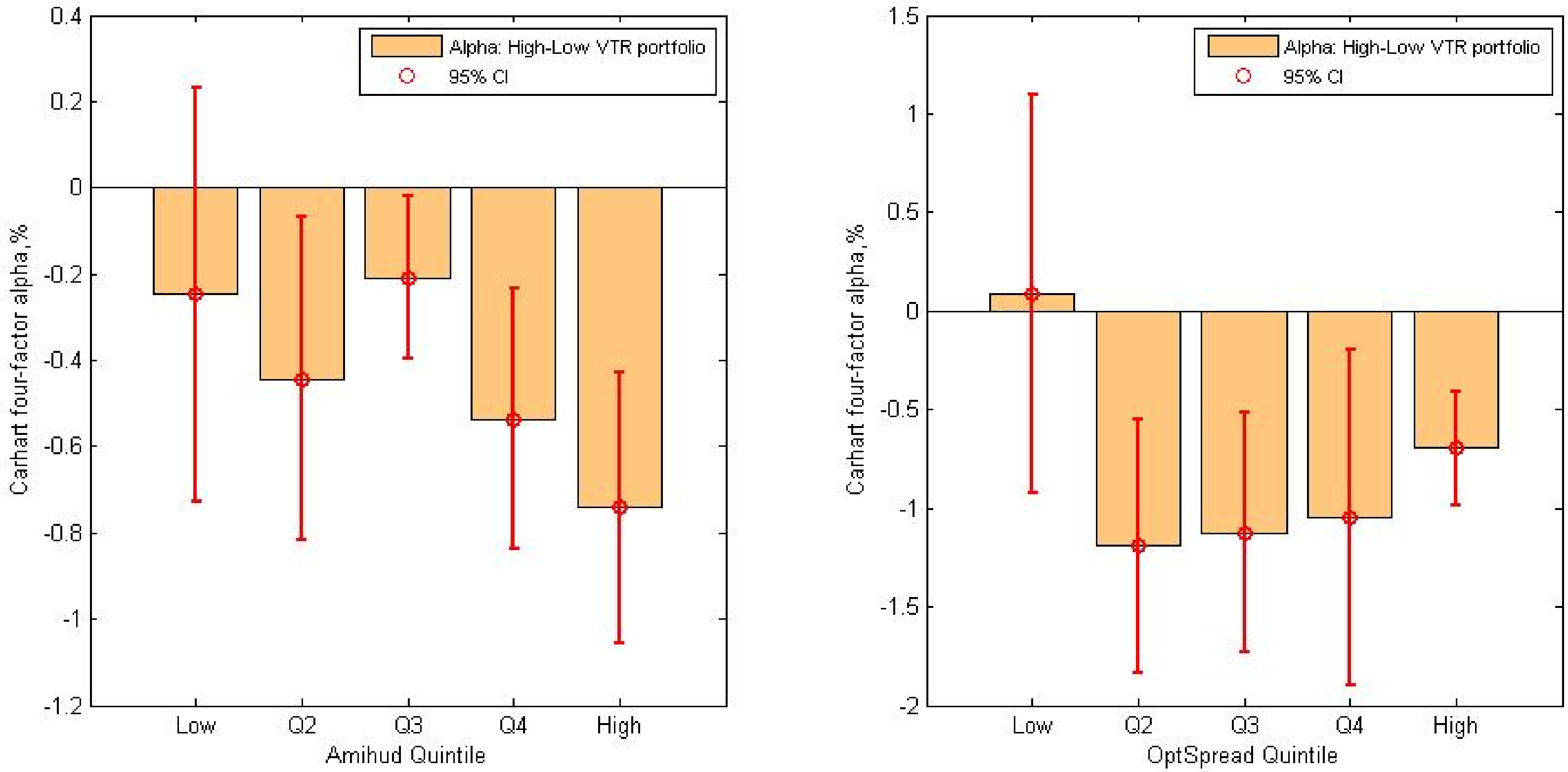

Figure 6. ***VTR* and Liquidity Concerns.** This figure reports the relation between VTR and illiquidity measure. Specifically, we measure illiquidity from 2 sides: stock illiquidity (measured by Amihud), and option illiquidity (measured by OptSpread). To address the concern that the negative relation between VTR and future stock return is driven by illiquidity, we conduct conditional double-sorting strategy and report the Carhart 4-factor alpha of long-short strategy. The sample period is from January 2004 to December 2014.

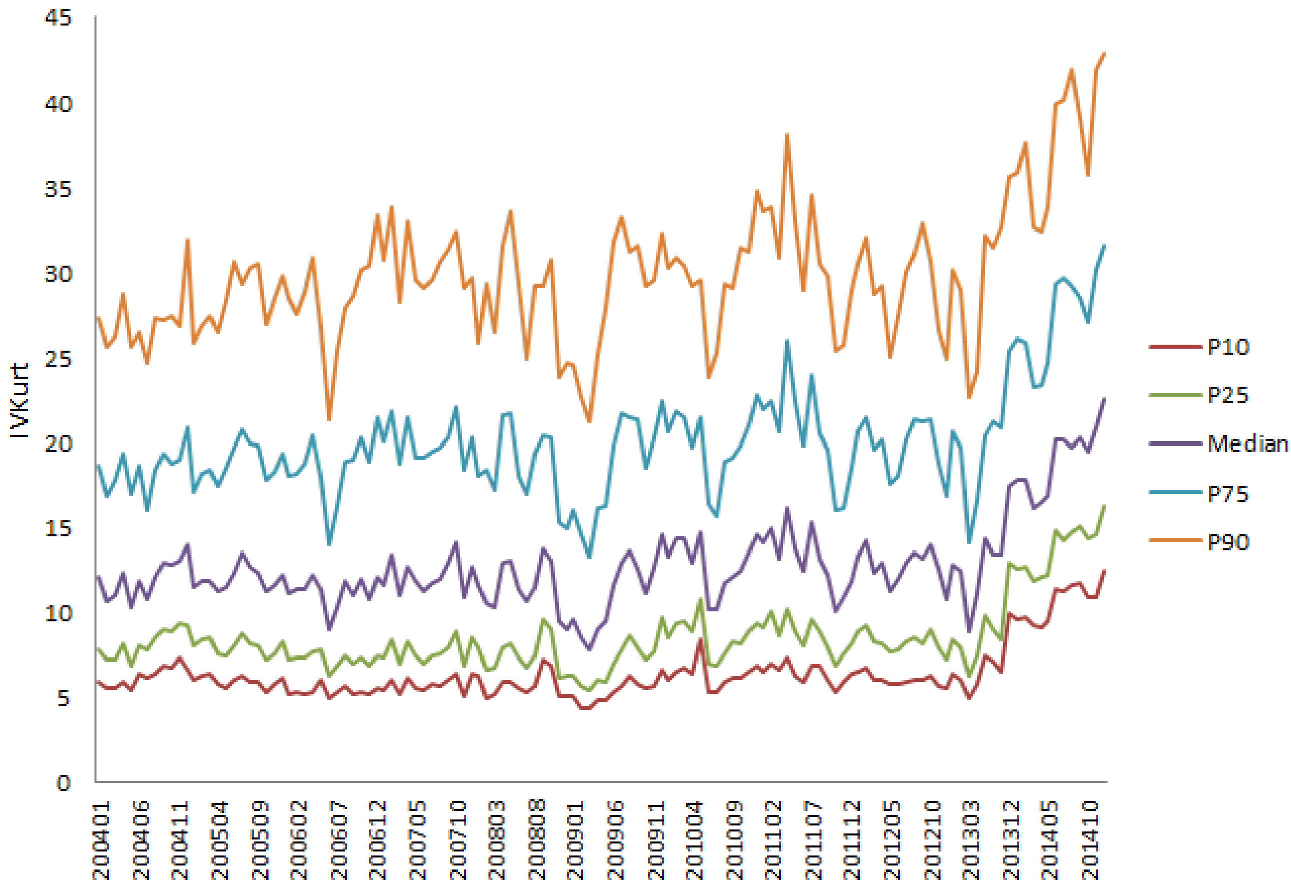

Figure 7. Cross-Sectional Percentiles of IV Kurtosis. This figure displays the distribution percentiles of IV Kurtosis for the cross-section of stocks by year-month. IV Kurtosis is measured using intraday quartic variations of the log change in IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. The sample consists of 156,509 firm-month observations over the time period January 2004 to December 2014.

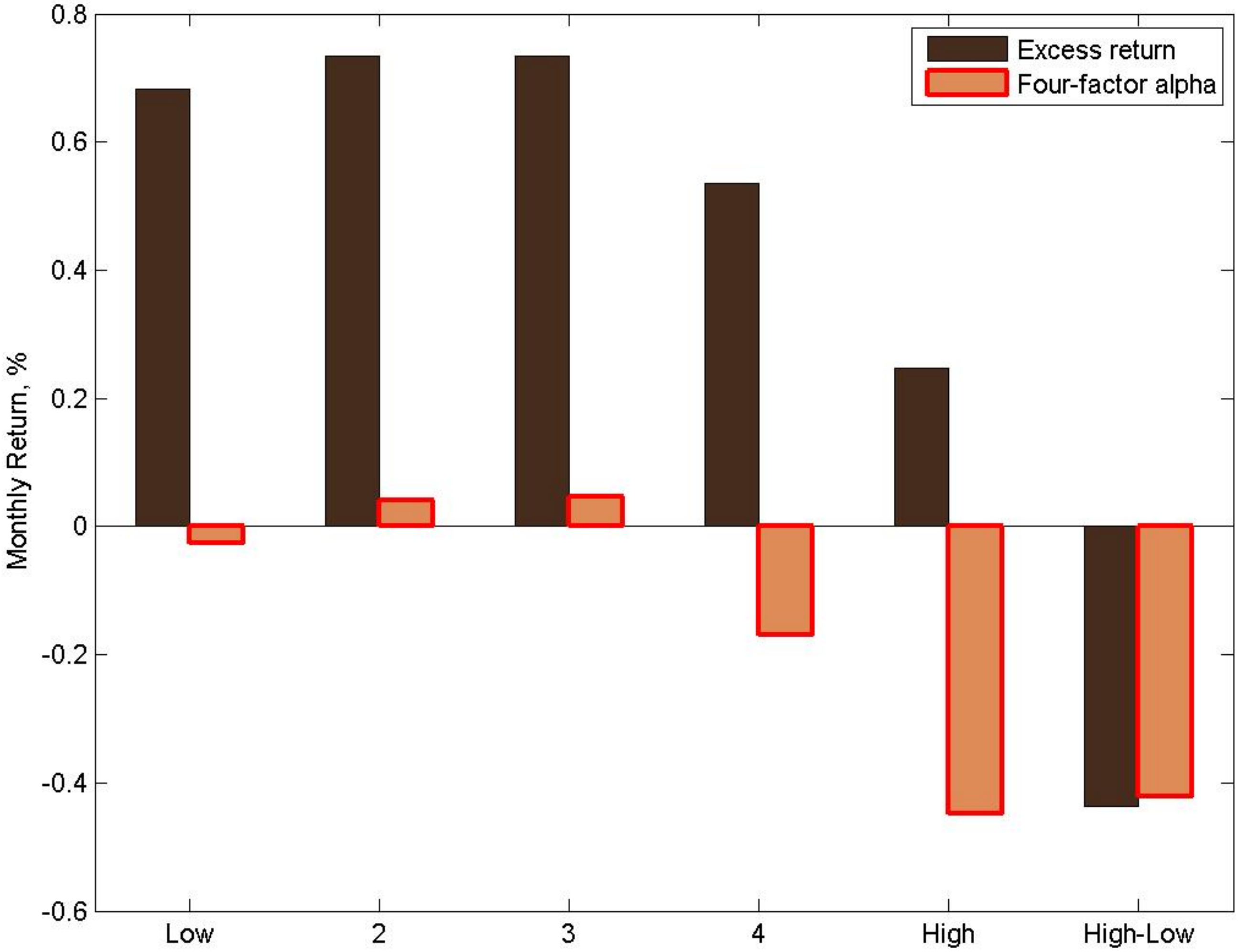

Figure 8. Monthly Performance of VTR Portfolios. This figure displays the average monthly excess return and four-factor alpha of portfolios sorted on VTR. VTR is the monthly tail risk measure of IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. By the end of each month, I sort stocks into quintile portfolios based on VTR. The sample period is from January 2004 to December 2014.

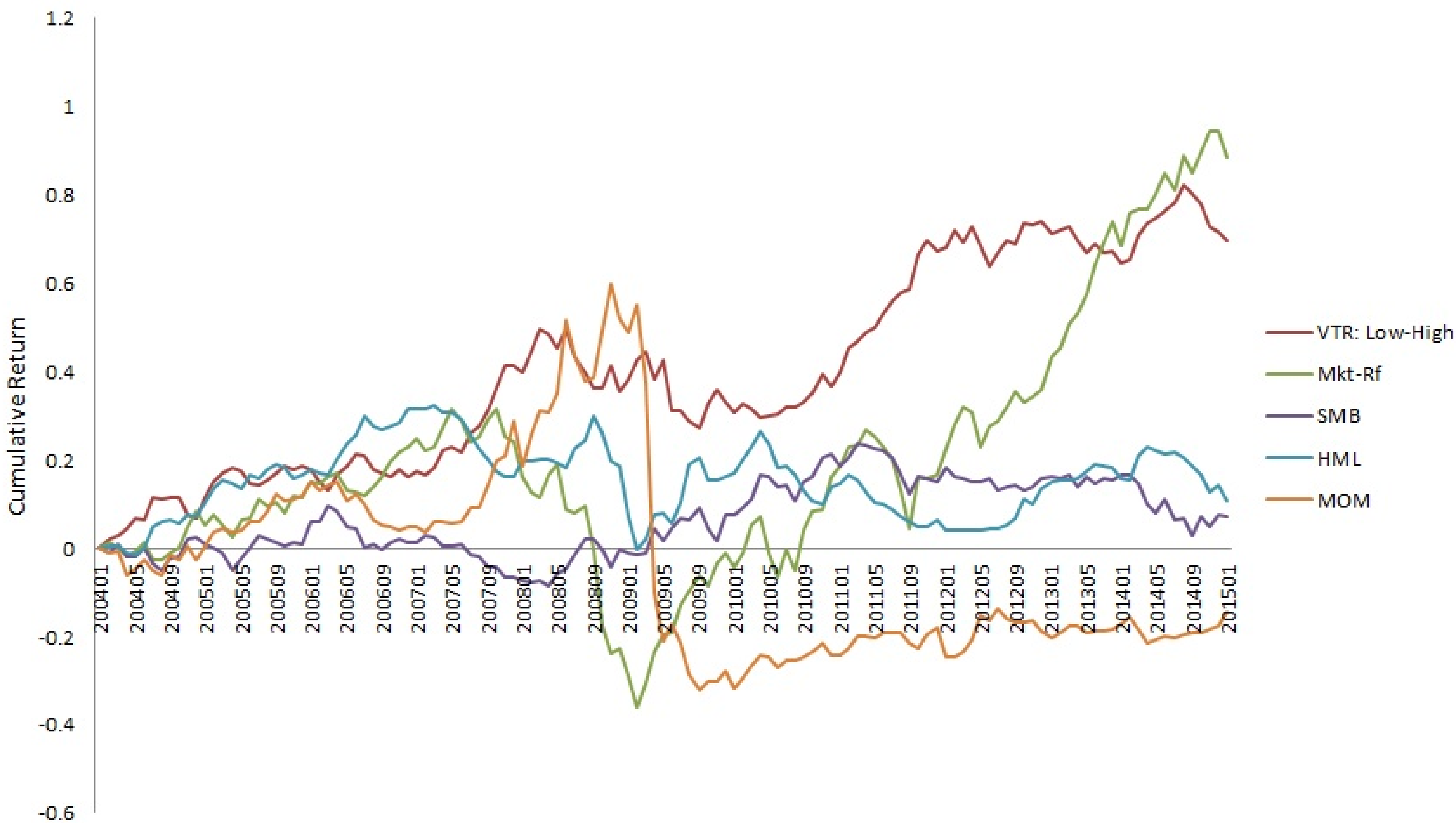

Figure 9. Cumulative Return Series. This figure plots the cumulative return series of long-short strategy in VTR, Fama-French 3 factors and Cahart Momentum factor. The long-short strategy in VTR holds a long position in the lowest quintile with a short position in the highest quintile sorted on the basis of VTR. The sample period is from January 2004 to December 2014.

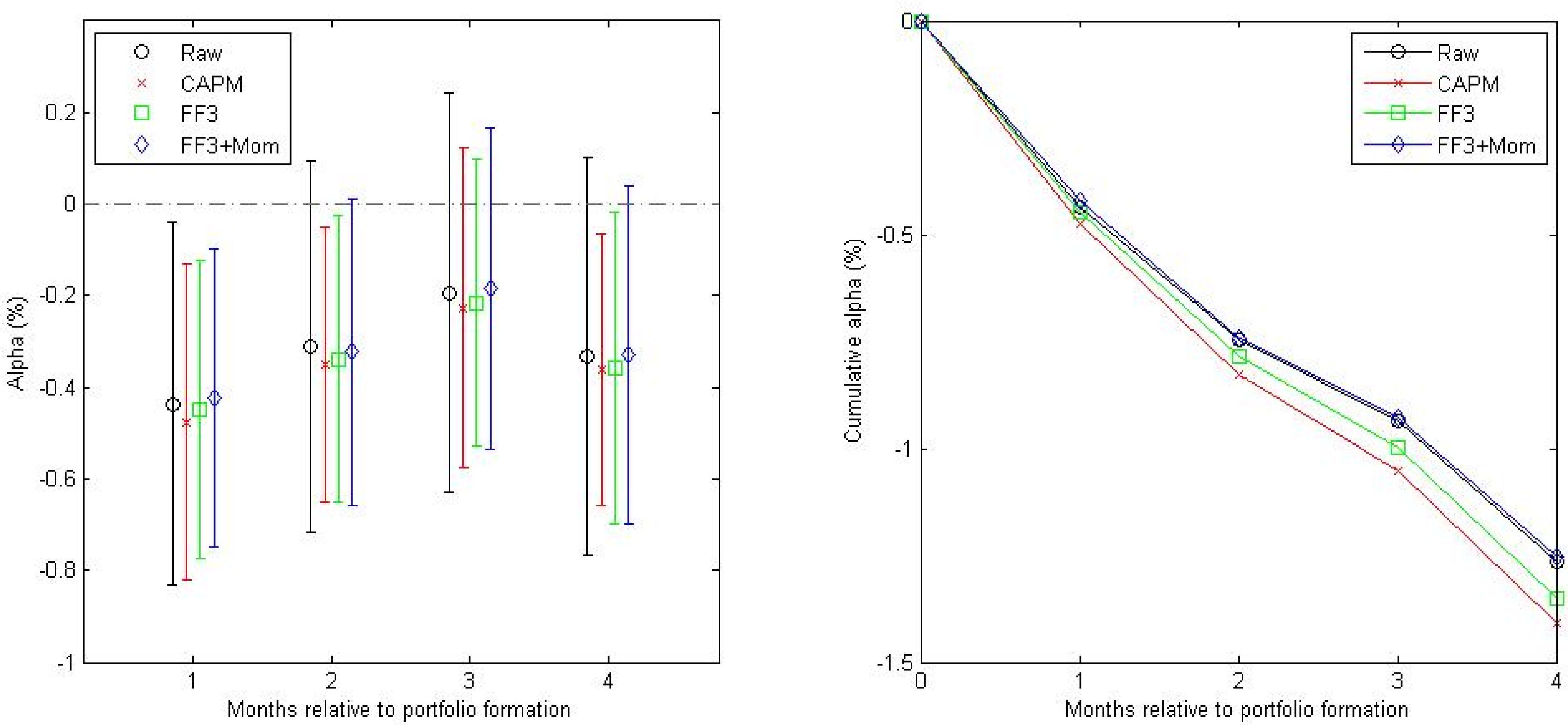

Figure 10. Performance Persistence of VTR-Return Relation. This figure presents the the alphas associated with a portfolio that combines an equal-weighted long position in the highest quintile with an equal-weighted short position in the lowest sorted on the basis of VTR. VTR is the monthly tail risk measure of IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. The left graph shows the monthly alphas, where the surrounding error bars represent 95% confidence interval. The right graph shows the cumulative alphas with respect to different benchmarks. The sample period is from January 2004 to December 2014.

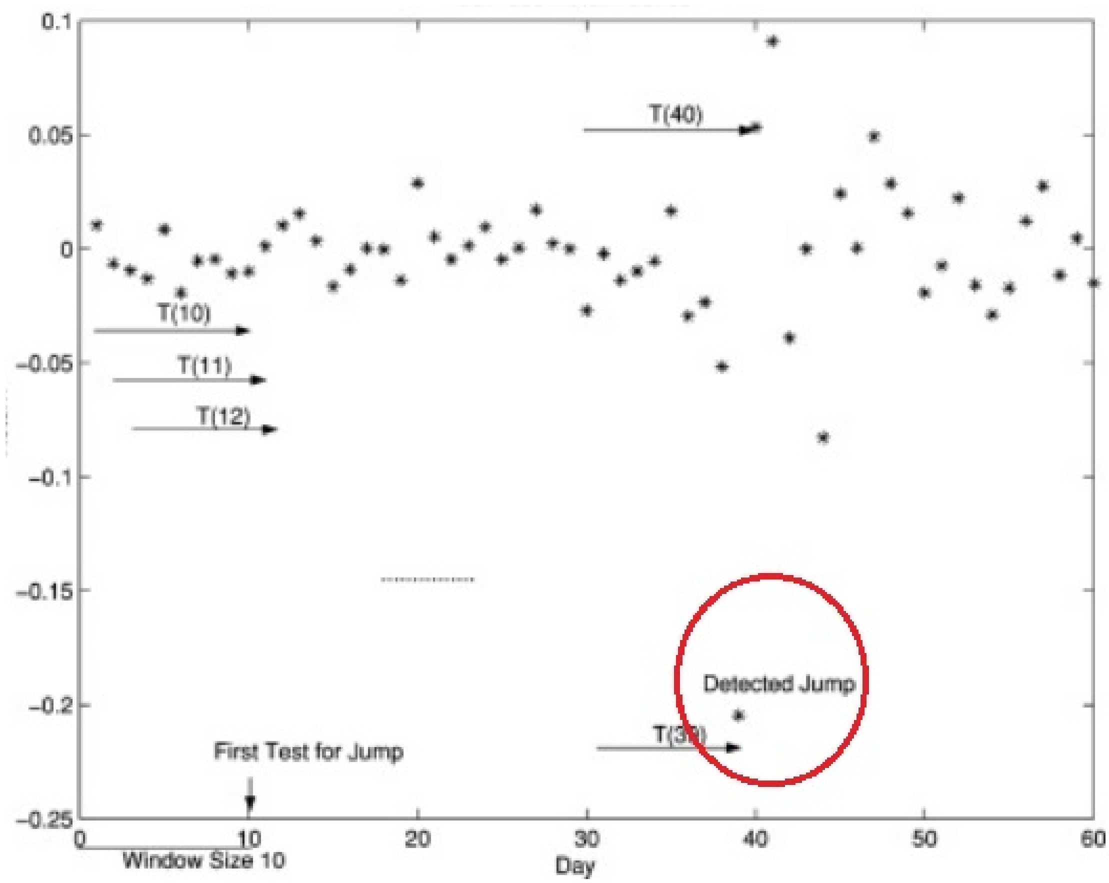

Figure 11. Lee and Mykland (2007) Non-Parametric Jump Identification Methodology. This figure is the original Figure 1 in Lee and Mykland (2007). This graph illustrated the intuition behind the non-parametric jump detection test.

Table I

Summary Statistics of VTR by Year

This table displays the volatility tail risk measure VTR by year. VTR is the monthly tail risk measure of IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. Entires to the table are the mean, standard deviation, 10th percentile, 25th percentile, median, 75th percentile, and 90th percentile of VTR across securities by year. The sample consists of 156,509 firm-month observations over the time period January 2004 to December 2014.

Year	Mean	Std. Dev.	P10	P25	P50	P75	P90
2004	0.7059	0.1023	0.5758	0.6281	0.6996	0.7749	0.8443
2005	0.7073	0.1063	0.5692	0.6273	0.7022	0.7796	0.8530
2006	0.6930	0.1092	0.5527	0.6070	0.6866	0.7699	0.8414
2007	0.6989	0.1036	0.5658	0.6187	0.6921	0.7725	0.8426
2008	0.6698	0.1016	0.5485	0.5913	0.6569	0.7350	0.8133
2009	0.6722	0.1074	0.5404	0.5884	0.6615	0.7463	0.8224
2010	0.6910	0.1042	0.5617	0.6120	0.6816	0.7616	0.8369
2011	0.6833	0.1078	0.5524	0.6000	0.6702	0.7550	0.8354
2012	0.6934	0.1091	0.5561	0.6087	0.6859	0.7686	0.8442
2013	0.7020	0.1042	0.5703	0.6222	0.6963	0.7722	0.8420
2014	0.7340	0.0837	0.6325	0.6745	0.7297	0.7897	0.8451
Average	0.6955	0.1036	0.5660	0.6162	0.6875	0.7659	0.8382

Table II

Characteristics of Portfolios Sorted by VTR

This table displays the characteristics of portfolios sorted by VTR. Each month, stocks are sorted by VTR into quintile portfolios and the equal-weighted characteristics of each portfolio are computed. VTR is the monthly tail risk measure of IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. Size is the market capitalization (in $billions). LBM is the log of book-to-market ratio. Reversal is the return of past month t. Momentum is return of past 6 month (from t−6 to t−1). MaxRet is the maximum daily return of past month t. HSkew is the historical skewness computed using past month's daily return. HKurt is the historical kurtosis computed using past month's daily return. Amihud is the Amihud (2002) illiquidity measure. iVol represents the idiosyncratic volatility relative to Fama-French 3 factor model defined in Ang et al. (2006). OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. OTMSkew is computed as the average of daily difference between the implied volatility of out-of-money puts and the implied volatility of at-the-money calls with around 30-day time-to-maturity. O/S is the option-to-stock volume ratio measured at monthly frequency. The sample period is from January 2004 to December 2014.

Quintiles	1 (Low)	2	3	4	5 (High)
VTR	0.5635	0.6321	0.6865	0.7459	0.8457
Size	2.0770	1.3747	0.9432	0.5646	0.2771
LBM	-0.9878	-0.9550	-0.9262	-0.9184	-0.9302
Reversal	0.0123	0.0125	0.0139	0.0136	0.0091
Momentum	0.0089	0.0090	0.0089	0.0102	0.0149
MaxRet	0.0475	0.0494	0.0520	0.0569	0.0635
HSkew	0.1044	0.1251	0.1396	0.1530	0.1690
HKurt	0.8881	1.2241	1.4006	1.6244	1.7931
Amihud	0.0007	0.0011	0.0013	0.0021	0.0038
iVol	0.0153	0.0161	0.0172	0.0191	0.0220
OptSpread	0.0894	0.1324	0.1694	0.2061	0.2335
ImpVol	0.3752	0.3817	0.3968	0.4268	0.4826
OTMSkew	0.0495	0.0531	0.0561	0.0618	0.0783
O/S	0.0018	0.0012	0.0010	0.0009	0.0011

Table III

Regressions of VTR on Firm Characteristics

This table explores the relation between VTR and other crucial firm characteristics. We perform contemporaneous regressions of VTR on other crucial firm controls. VTR is the monthly volatility tail risk measure. $ERJM$ is the equity return jump measure. VRP is the volatility risk premium proxy. Size is the market capitalization (in $billions). LBM is the log of book-to-market ratio. Reversal is the return of past month t. Momentum is return of past 6 month (from t−6 to t−1). MaxRet is the maximum daily return of past month t. Amihud is the Amihud (2002) illiquidity measure. iVol represents the idiosyncratic volatility relative to Fama-French 3 factor model defined in Ang et al. (2006). OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. *All variables are standardized.* The Newey-West (1987) t-statistics are reported in square brackets.

	Dependents: VTR_t															
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16
$ERJM$	0.473															0.038
	[8.20]															[1.00]
VRP		0.192														0.112
		[9.63]														[11.01]
Size			-0.4													-0.155
			[-11.75]													[-5.26]
LBM				-0.003												-0.016
				[-0.23]												[-2.13]
Reversal					-0.013											-0.058
					[-1.93]											[-2.23]
Momentum						0.028										-0.092
						[5.89]										[-3.37]
MaxRet							0.14									-0.176
							[9.28]									[-10.94]
iVol								0.204								0.172
								[10.71]								[8.56]
HSKew									0.012							0.063
									[3.13]							[7.14]
HKurt										0.129						0.075
										[11.41]						[9.50]
RVolKurt											0.099					0.061
											[4.63]					[7.89]
Amihud												0.408				0.12
												[10.07]				[7.28]
ImpVol													0.271			-0.081
													[7.65]			[-2.61]
OTMSkew														0.239		0.092
														[11.25]		[9.87]
OptSpread															0.493	0.347
															[9.12]	[9.50]
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. $R^2(\%)$	4.45	3.41	18.46	0.23	0.31	0.37	1.58	3.7	0.09	1.59	1.1	12.22	5.29	4.28	22.6	33.18

Table IV

VAR Analysis

This table reports the VAR analysis of predicting future firm characteristics. VTR is the monthly volatility tail risk measure. $ERJM$ is the equity return jump measure. VRP is the volatility risk premium proxy. SktRet is the monthly stock return. MaxRet is the maximum daily return of past month t. Amihud is the Amihud (2002) illiquidity measure. iVol represents the idiosyncratic volatility relative to Fama-French 3 factor model defined in Ang et al. (2006). HSkew is the historical skewness computed using past month's daily return. HKurt is the historical kurtosis computed using past month's daily return. OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. OTMSkew is computed as the average of daily difference between the implied volatility of out-of-money puts and the implied volatility of at-the-money calls with around 30-day time-to-maturity. *All variables are standardized.* The Newey-West (1987) t-statistics are reported in square brackets.

	Dependents: X^i_{t+1}												
	VTR	$ERJM$	VRP	StkRet	MaxRet	iVol	HSkew	HKurt	RVolKurt	Amihud	ImpVol	OTMSkew	OptSpread
VTR	0.439	0.016	0.044	-0.007	0.002	0.021	0.008	0.038	0.026	0.017	0.005	0.045	0.085
	[26.55]	[2.78]	[5.48]	[-2.56]	[0.39]	[2.33]	[1.55]	[4.56]	[4.53]	[4.95]	[0.81]	[5.49]	[10.01]
$ERJM$	0.064	0.362	-0.041	0.01	0.033	0.062	-0.014	-0.144	-0.082	0.125	0.086	0.119	-0.015
	[1.54]	[13.42]	[-1.32]	[1.11]	[2.45]	[2.63]	[-1.65]	[-6.35]	[-1.58]	[9.60]	[3.56]	[7.19]	[-1.31]
VRP	0.085	-0.003	0.162	0.014	0.02	0.039	0.023	0.114	0.057	0.063	0.035	-0.005	0.008
	[4.16]	[-0.38]	[12.24]	[1.05]	[4.65]	[7.18]	[5.15]	[16.41]	[3.98]	[7.49]	[6.43]	[-0.81]	[1.84]
StkRet	-0.016	-0.016	0.032	-0.009	-0.046	-0.026	-0.037	-0.016	0.003	-0.041	-0.023	-0.02	-0.034
	[-3.78]	[-1.51]	[2.59]	[-0.84]	[-3.67]	[-3.02]	[-4.17]	[-1.49]	[0.35]	[-15.72]	[-4.29]	[-2.87]	[-10.67]
MaxRet	-0.076	-0.015	-0.043	0.027	0.009	-0.1	0.006	-0.019	0.01	-0.062	-0.004	-0.02	0.009
	[-6.14]	[-1.07]	[-2.36]	[2.32]	[0.31]	[-4.86]	[0.47]	[-1.93]	[1.37]	[-7.11]	[-0.31]	[-1.73]	[0.92]
iVol	0.081	0.001	0.133	-0.009	0.031	0.15	0.029	0.019	-0.036	0.039	0.087	-0.018	-0.036
	[16.42]	[0.05]	[8.93]	[-0.39]	[2.98]	[7.23]	[2.90]	[1.26]	[-2.10]	[6.15]	[15.56]	[-1.50]	[-5.30]
HSkew	0.026	0.007	0.017	-0.009	0.004	0.037	0.021	0.02	-0.006	0.019	0.003	0.011	-0.001
	[6.02]	[1.40]	[2.80]	[-2.37]	[0.49]	[7.44]	[5.72]	[4.13]	[-1.92]	[5.83]	[0.31]	[3.09]	[-0.43]
HKurt	0.018	-0.02	0.02	0.001	-0.038	-0.05	0.008	0.014	-0.008	0.034	-0.052	0.001	0.024
	[3.20]	[-5.64]	[3.34]	[0.23]	[-3.13]	[-6.64]	[2.16]	[2.26]	[-5.85]	[4.88]	[-9.11]	[0.24]	[6.50]
RVolKurt	-0.019	-0.028	0.018	0.004	-0.022	-0.036	0.004	-0.016	0.046	-0.006	-0.026	-0.007	0.017
	[-1.82]	[-4.74]	[2.64]	[1.58]	[-4.26]	[-4.67]	[2.61]	[-3.41]	[2.04]	[-1.33]	[-4.87]	[-1.11]	[2.76]
Amihud	0.087	0.027	0.038	0.028	0.022	0.025	0.02	0.02	-0.009	0.814	0.02	0.004	0.068
	[7.20]	[3.10]	[9.51]	[4.24]	[4.15]	[9.11]	[5.76]	[3.16]	[-1.11]	[41.53]	[9.55]	[0.83]	[11.31]
ImpVol	-0.035	0.227	0.321	-0.02	0.409	0.518	0.002	0.068	-0.065	-0.038	0.745	0.126	0.015
	[-0.63]	[16.23]	[14.08]	[-1.74]	[22.44]	[18.77]	[0.16]	[3.00]	[-2.02]	[-4.19]	[72.96]	[7.00]	[1.98]
OTMSkew	0.043	0.051	0.004	-0.019	0.02	0.039	-0.008	0.01	0	-0.002	0.032	0.547	-0.009
	[16.27]	[8.55]	[0.17]	[-5.12]	[3.43]	[14.10]	[-1.66]	[1.78]	[0.04]	[-0.44]	[3.29]	[18.00]	[-1.28]
OptSpread	0.212	0.006	0.002	0.012	0.013	0.005	0.003	0.017	0.043	0.027	0.011	0.001	0.744
	[5.03]	[2.47]	[0.28]	[4.01]	[3.26]	[1.12]	[1.01]	[3.20]	[3.51]	[4.45]	[3.80]	[0.38]	[30.15]
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. $R^2(\%)$	43.2	56.16	26.43	6.41	25.17	38.23	1.34	3.68	3.78	79.54	79.66	44.78	68.92

Table V

VTR and IV Jump Measures, IVJI/IVJS/IVSJS

This table conducts deep analysis on the relation between our constructed volatility tail risk measure, VTR, and IV jump measures, constructed using Lee and Mykland (2007) non-parametric identification approach. I include three measures of IV jumps: IVJI, IVJS, and IVSJS. IVJI represents IV jump intensity. IVJS represents IV jump size. IVSJS represents IVSJS represents IV scaled jump size. VTR is the monthly volatility tail risk measure. $ERJM$ is the equity return jump measure. VRP is the volatility risk premium proxy. Size is the market capitalization (in $billions). LBM is the log of book-to-market ratio. Reversal is the return of past month t. Momentum is return of past 6 month (from t−6 to t−1). MaxRet is the maximum daily return of past month t. Amihud is the Amihud (2002) illiquidity measure. iVol represents the idiosyncratic volatility relative to Fama-French 3 factor model defined in Ang et al. (2006). OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. **Panel A** reports the average cross-sectional correlation matrix between VTR and IVJI/IVJS/IVSJS. **Panel B** reports forecasting regressions using VTR and other crucial controls to predict future IVJI/IVJS/IVSJS. *All variables are standardized.* The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

Panel A: Cross-Sectional Correlation between VTR and IVJI/IVJS/IVSJS

	VTR	IVJI	IVJS	IVSJS
VTR	1			
IVJI	0.406	1		
IVJS	0.408	0.237	1	
IVSJS	0.591	0.088	0.452	1

	Panel B: Forecasting Future IV Jump Measures					
	$IVJI_{t+1}$	$IVJS_{t+1}$	$IVSJS_{t+1}$	$IVJI_{t+1}$	$IVJS_{t+1}$	$IVSJS_{t+1}$
VTR	0.381	0.325	0.394	0.252	0.105	0.265
	[19.22]	[18.52]	[25.31]	[13.87]	[7.92]	[24.35]
$ERJM$				-0.032	0.15	0.055
				[-1.18]	[8.47]	[2.60]
VRP				0.087	-0.052	0.041
				[8.50]	[-6.87]	[2.86]
Size				-0.034	-0.085	0.017
				[-3.99]	[-2.45]	[1.23]
LBM				0.014	0.037	-0.016
				[4.88]	[4.36]	[-3.46]
Reversal				-0.15	0	0.016
				[-9.39]	[0.02]	[0.92]
Momentum				-0.108	0.001	0.019
				[-6.49]	[0.09]	[1.18]
MaxRet				-0.01	-0.02	-0.02
				[-0.64]	[-1.67]	[-0.93]
iVol				0.013	-0.081	0.039
				[1.05]	[-7.88]	[3.39]
HSKew				-0.002	0.005	0.008
				[-0.30]	[1.18]	[0.99]
HKurt				0.013	0.041	0.01
				[2.35]	[5.39]	[1.25]
VoV				-0.009	-0.006	0.008
				[-1.71]	[-1.31]	[1.19]
RVolKurt				-0.014	0.007	-0.013
				[-4.01]	[1.28]	[-1.68]
Amihud				0.052	0.041	0.047
				[2.70]	[4.61]	[4.49]
ImpVol				0.01	-0.178	-0.007
				[0.47]	[-7.77]	[-0.23]
OTMSkew				0.026	0.04	0.049
				[2.77]	[7.03]	[7.05]
OptSpread				0.172	0.141	0.2
				[9.88]	[19.38]	[12.85]
O/S				-0.062	-0.093	0.025
				[-7.55]	[-13.24]	[1.48]
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Time-Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2(%)	15.96	12.93	16.5	22.86	41.02	22.92

Table VI

Market Return Predictability

This table reports market return predictability test using VTR and other well-documented predictors. VTR is the monthly volatility tail risk measure. $ERJM$ is the equity return jump measure. VRP is the volatility risk premium proxy. D/P is the monthly dividend-price ratio. The Newey-West (1987) t-statistics are reported in square brackets.

	Horizon: 1-month					Horizon: 3-month					Horizon: 6-month				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5
VTR	-0.049				-0.032	-0.158				-0.122	-0.293				-0.254
	[-1.698]				[-1.479]	[-2.494]				[-1.317]	[-2.248]				[-1.173]
$ERJM$		-0.917			-0.406		-1.913			-0.900		-0.162			1.129
		[-4.625]			[-1.548]		[-3.475]			[-1.462]		[-0.163]			[0.967]
VRP			6.403		5.394			13.443		10.807			12.576		13.300
			[4.054]		[2.529]			[3.350]		[3.115]			[2.041]		[1.914]
D/P				0.002	0.002				0.001	0.001				0.004	0.005
				[1.638]	[2.024]				[0.513]	[0.711]				[0.976]	[1.301]
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2(%)	0.40	4.33	10.54	-0.60	9.71	2.96	5.32	12.85	-0.94	13.66	4.67	-0.97	4.04	-0.74	6.67

Table VII

VTR, Option Returns and Volatility Risk Premium

This table reports average Fama-MacBeth (1973) regression slopes and t-values from cross-sectional regressions that predict option returns and variance risk premium using volatility tail risk measure, VTR. $OptRet^{straddle}_{avg}$ is the average daily option straddle return for each stock in a given month. $OptRet^{straddle}_{avg}$ is the aggregated daily option straddle return for each stock in a given month. We adjust the number of put option in each option straddle pair such that the straddle is risk-neutral. VRP, the variance risk premium (or volatility risk premium), is measured as the difference between implied volatility and realized volatility. The sample consists of 156,509 firm-month observations over the time period January 2004 to December 2014. The Newey-West (1987) t-statistics are reported in square brackets.

Model: $Y^i_{t+1} = \alpha + \beta VTR^i_t + \epsilon^i_{t+1}$

	Dependents: Y		
	$OptRet^{straddle}_{avg}$, %	$OptRet^{straddle}_{sum}$, %	VRP=IV-RV
Intercept	-1.2123	-24.3213	-0.0357
	[-1.716]	[-1.745]	[-4.066]
VTR	2.0191	40.7523	0.0779
	[1.786]	[1.870]	[16.642]
Avg.R^2(%)	0.30	0.27	0.45

Table VIII

Correlation Matrix

Panel A displays average cross-sectional correlations of firm characteristics. Size is the market capitalization (in $billions). LBM is the log of book-to-market ratio. Reversal is the return of past month t. Momentum is return of past 6 month (from t−6 to t−1). MaxRet is the maximum daily return of past month t. HSkew is the historical skewness computed using past month's daily return. HKurt is the historical kurtosis computed using past month's daily return. Amihud is the Amihud (2002) illiquidity measure. iVol represents the idiosyncratic volatility relative to Fama-French 3 factor model defined in Ang et al. (2006). OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. OTMSkew is computed as the average of daily difference between the implied volatility of out-of-money puts and the implied volatility of at-the-money calls with around 30-day time-to-maturity. O/S is the option-to-stock volume ratio measured at monthly frequency. The sample period is from January 2004 to December 2014.

Panel A: Average Cross-Sectional Correlations of Firm Characteristics

	VTR	Size	LBM	Reversal	Momentum	MaxRet	HSkew	HKurt	Amihud	iVol	OptSpread	ImpVol	OTMSkew	O/S
VTR	1													
Size	-0.419	1												
LBM	0.026	-0.052	1											
Reversal	-0.011	-0.027	0.012	1										
Momentum	0.014	-0.045	0.004	-0.872	1									
MaxRet	0.133	-0.315	-0.028	0.404	-0.257	1								
HSkew	0.024	-0.037	-0.013	0.447	-0.423	0.517	1							
HKurt	0.112	-0.097	-0.051	0.035	0.041	0.504	0.134	1						
Amihud	0.279	-0.451	0.005	-0.008	0.009	0.192	0.027	0.023	1					
iVol	0.201	-0.415	-0.059	0.078	0.090	0.801	0.087	0.504	0.252	1				
OptSpread	0.448	-0.472	0.102	0.011	-0.012	0.053	0.019	0.043	0.344	0.069	1			
ImpVol	0.241	-0.572	-0.073	-0.041	0.121	0.500	0.026	0.109	0.379	0.655	0.088	1		
OTMSkew	0.211	-0.243	-0.006	-0.006	0.038	0.198	0.009	0.049	0.216	0.264	0.134	0.361	1	
O/S	-0.126	0.197	-0.165	0.016	0.008	0.060	0.023	0.025	-0.044	0.082	-0.335	0.130	0.119	1

Panel B displays unconditional correlations of alternative volatility tail risk measures. IV Kurtosis (IVKurt) is measured using intraday quartic variations of the log change in IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. λ^{LT} is the left-tail risk measure of IV using power-law approach. λ^{RT} is the right-tail risk measure of IV using power-law approach. The sample period is from January 2004 to December 2014.

Panel B: Correlations of Alternative Volatility Tail Risk Measures

	VTR	IVKurt	λ^{LT}	λ^{RT}
VTR	1			
IVKurt	0.668	1		
λ^{LT}	0.678	0.585	1	
λ^{RT}	0.687	0.572	0.922	1

Table IX

Volatility Tail Risk and the Cross-Section of Stock Returns

This table displays the equal-weighted monthly portfolio returns (in percentage) formed on the basis of VTR ($VLTR$ and $VRTR$). Quintile portfolios are formed by then end of each month, ranging from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. Panel A reports results for VTR. Panel B reports results for $VLTR$. Panel C reports results for $VRTR$. $VLTR$ ($VRTR$) is the left-tail (right-tail) risk measure of IV, where VTR=$VLTR$+$VRTR$. The sample consists of 156,509 firm-month observations over the time period January 2004 to December 2014. The raw alphas (in percentage) are obtained from quintile portfolios sorted on tail risk measure, VTR ($VLTR$ and $VRTR$). The risk-adjusted alphas (CAPM, FF3, and FF3+MOM) are the intercepts from time-series regressions of the returns of the portfolio on systematic risk factors. The Newey-West (1987) t-statistics are reported in square brackets.

	1 (Low)	2	3	4	5 (High)	High−Low	(4+5)−(1+2)
Panel A: VTR and the Cross-Section of Stock Returns							
Raw return	0.683	0.733	0.735	0.535	0.247	-0.436	-0.317
	[1.507]	[1.518]	[1.343]	[1.008]	[0.494]	[-2.405]	[-3.244]
Alpha, CAPM	-0.054	-0.011	0.007	-0.222	-0.53	-0.476	-0.344
	[-0.29]	[-0.06]	[0.074]	[-1.799]	[-2.009]	[-2.737]	[-3.923]
Alpha, FF3	-0.028	0.019	0.043	-0.179	-0.476	-0.448	-0.323
	[-0.233]	[0.218]	[0.519]	[-2.39]	[-3.367]	[-2.715]	[-2.994]
Alpha, FF3+MOM	-0.025	0.04	0.047	-0.169	-0.447	-0.422	-0.315
	[-0.223]	[0.526]	[0.552]	[-1.92]	[-3.508]	[-2.665]	[-2.807]
Panel B: $VLTR$ and the Cross-Section of Stock Returns							
Raw return	0.634	0.822	0.762	0.426	0.291	-0.343	-0.37
	[1.438]	[1.612]	[1.453]	[0.788]	[0.586	[-1.997]	[-4.77]
Alpha, CAPM	-0.106	0.08	0.032	-0.312	-0.504	-0.398	-0.395
	[-0.544]	[0.568]	[0.272]	[-2.917]	[-1.787]	[-2.358]	[-5.559]
Alpha, FF3	-0.077	0.112	0.066	-0.27	-0.451	-0.374	-0.378
	[-0.609]	[2.734]	[0.846]	[-3.097]	[-3.098]	[-2.622]	[-4.963]
Alpha, FF3+MOM	-0.073	0.135	0.071	-0.268	-0.418	-0.345	-0.374
	[-0.609]	[5.102]	[0.876]	[-2.994]	[-3.348]	[-2.787]	[-4.903]

	1 (Low)	2	3	4	5 (High)	High−Low	(4+5)−(1+2)
Panel C: $VRTR$ and the Cross-Section of Stock Returns							
Raw return	0.673	0.737	0.617	0.541	0.368	-0.305	-0.251
	[1.438]	[1.534]	[1.185]	[1.003]	[0.738]	[-1.99]	[-2.022]
Alpha, CAPM	-0.067	0	-0.136	-0.213	-0.393	-0.326	-0.27
	[-0.372]	[0.001]	[-0.993]	[-1.612]	[-1.903]	[-2.187]	[-2.277]
Alpha, FF3	-0.041	0.03	-0.098	-0.167	-0.344	-0.303	-0.25
	[-0.359]	[0.32]	[-1.198]	[-2.475]	[-2.9]	[-1.869]	[-1.733]
Alpha, FF3+MOM	-0.04	0.047	-0.083	-0.154	-0.322	-0.282	-0.241
	[-0.371]	[0.545]	[-0.895]	[-2.014]	[-2.73]	[-1.703]	[-1.63]

Table X

Stock Return Predictability

This table displays Fama-MacBeth regression results of monthly returns on VTR and other control variables. VTR is the monthly volatility tail risk measure. $ERJM$ is the equity return jump measure. VRP represents volatility risk premium. Size is the market capitalization (in $billions). LBM is the log of book-to-market ratio. Reversal is the return of past month t. Momentum is return of past 6 month (from t−6 to t−1). MaxRet is the maximum daily return of past month t. HSkew is the historical skewness computed using past month's daily return. HKurt is the historical kurtosis computed using past month's daily return. Amihud is the Amihud (2002) illiquidity measure. iVol represents the idiosyncratic volatility relative to Fama-French 3 factor model defined in Ang et al. (2006). OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. OTMSkew is computed as the average of daily difference between the implied volatility of out-of-money puts and the implied volatility of at-the-money calls with around 30-day time-to-maturity. O/S is the option-to-stock volume ratio measured at monthly frequency. The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VTR	-0.0168			-0.0067	-0.0089	-0.0116
	[-5.66]			[-3.09]	[-2.57]	[-2.77]
$ERJM$		-0.0837		-0.0744	-0.0175	-0.0015
		[-4.81]		[-4.84]	[-0.99]	[-0.12]
VRP			-0.1908	-0.0584	-0.1486	0.0684
			[-1.62]	[-0.50]	[-1.08]	[0.39]
Size					-0.0007	-0.0016
					[-1.46]	[-2.04]
LBM					0.0007	0.0003
					[0.78]	[0.26]
Reversal					0.0101	0.0148
					[0.53]	[0.71]
Momentum					0.013	0.0241
					[0.56]	[1.16]
MaxRet					-0.0042	0.0676
					[-0.11]	[1.59]
iVol					-0.2531	-0.136
					[-1.65]	[-0.70]
HSkew					0.0003	-0.0008
					[0.55]	[-1.53]
HKurt					0.0008	0.0003
					[4.49]	[2.07]
Amihud					-0.129	-0.1967
					[-0.60]	[-0.65]
ImpVol						-0.0314
						[-3.98]
OTMSkew						-0.0537
						[-7.31]
OptSpread						-0.0008
						[-0.22]
O/S						0.3255
						[1.29]
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2(%)	0.37	1.82	0.92	2.72	6.94	8.13

Table XI

VTR Decompositions and Return Predictability

This table displays Fama-MacBeth regression results of monthly returns on VTR and other control variables. VTR is the monthly volatility tail risk measure. I decompose individual stock VTR into systematic VTR, $sVTR$, and idiosyncratic VTR, $iVTR$, by projecting stock VTR onto SPY VTR (systematic volatility tail risk measure). The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

	Model 1	Model 2	Model 3	Model 4	Model 5
$sVTR$	-0.0757		-0.1507		-0.1441
	[-5.510]		[-4.277]		[-4.426]
$iVTR$		0.0451		0.0482	0.0332
		[2.936]		[3.253]	[3.187]
$ERJM$			0.0032	-0.0019	0.0051
			[0.097]	[-0.057]	[0.155]
VRP			0.0942	-0.1293	0.0688
			[0.689]	[-0.756]	[0.495]
Size			-0.0038	-0.0014	-0.0038
			[-3.906]	[-2.585]	[-4.020]
LBM			-0.0006	-0.0001	-0.0007
			[-0.504]	[-0.051]	[-0.577]
Reversal			0.0026	0.0086	0.0046
			[0.088]	[0.283]	[0.161]
Momentum			0.0205	0.0277	0.024
			[0.759]	[0.950]	[0.904]
MaxRet			0.0662	0.1209	0.0755
			[1.585]	[2.423]	[1.749]
iVol			-0.1075	-0.3087	-0.1442
			[-0.809]	[-1.803]	[-1.090]
HSkew			-0.0002	-0.0011	-0.0004
			[-0.439]	[-1.809]	[-0.694]
HKurt			0.0004	0.0001	0.0003
			[1.663]	[0.415]	[1.472]
Amihud			0.4445	-0.0486	0.4034
			[0.912]	[-0.129]	[0.870]
ImpVol			-0.0272	-0.0231	-0.0267
			[-3.483]	[-2.654]	[-3.345]
OTMSkew			-0.0287	-0.0521	-0.0307
			[-2.266]	[-3.896]	[-2.479]
OptSpread			0.0305	-0.0095	0.0244
			[4.765]	[-1.659]	[4.935]
O/S			-0.2729	-0.0216	-0.2436
			[-1.990]	[-0.110]	[-1.738]
Intercept	Yes	Yes	Yes	Yes	Yes
Adj. $R^2(\%)$	0.81	0.32	8.78	8.02	8.89

Table XII

Alternative Volatility Tail Risk Measure and the Cross-Section of Stock Returns

This table displays the equal-weighted monthly portfolio returns (in percentage) formed on the basis of IV Kurtosis (IVKurt) (λ^{LT} and λ^{RT}). Quintile portfolios are formed by then end of each month, ranging from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. Panel A reports results for IVKurt. Panel B reports results for λ^{LT}. Panel C reports results for λ^{RT}. IV Kurtosis (IVKurt) is measured using intraday quartic variations of the log change in IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. λ^{LT} (λ^{RT}) is the left-tail (right-tail) risk measure of IV using power-law approach.. The sample consists of 156,509 firm-month observations over the time period January 2004 to December 2014. The raw alphas (in percentage) are obtained from quintile portfolios sorted on tail risk measure, IVKurt (λ^{LT} and λ^{RT}). The risk-adjusted alphas (CAPM, FF3, and FF3+MOM) are the intercepts from time-series regressions of the returns of the portfolio on systematic risk factors. The Newey-West (1987) t-statistics are reported in square brackets.

	1 (Low)	2	3	4	5 (High)	High−Low	(4+5)−(1+2)
Panel A: IV Kurtosis (IVKurt) and the Cross-Section of Stock Returns							
Raw return	0.647	0.745	0.796	0.408	0.338	-0.308	-0.323
	[1.364]	[1.427]	[1.631]	[0.76]	[0.707]	[-2.347]	[-3.411]
Alpha, CAPM	-0.106	-0.014	0.046	-0.337	-0.399	-0.293	-0.308
	[-0.594]	[-0.102]	[0.243]	[-2.419]	[-2.126]	[-2.329]	[-3.42]
Alpha, FF3	-0.08	0.019	0.084	-0.294	-0.349	-0.27	-0.291
	[-0.738]	[0.307]	[1.117]	[-3.29]	[-3.452]	[-1.815]	[-2.684]
Alpha, FF3+MOM	-0.073	0.04	0.104	-0.289	-0.335	-0.262	-0.296
	[-0.724]	[0.557]	[1.628]	[-3.142]	[-3.271]	[-1.756]	[-2.815]
Panel B: λ^{LT} and the Cross-Section of Stock Returns							
Raw return	0.639	0.823	0.677	0.447	0.351	-0.288	-0.332
	[1.393]	[1.627]	[1.275]	[0.887]	[0.682]	[-1.748]	[-3.504]
Alpha, CAPM	-0.126	0.087	-0.057	-0.27	-0.441	-0.315	-0.336
	[-0.558]	[0.667]	[-0.466]	[-2.18]	[-1.729]	[-1.944]	[-3.728]
Alpha, FF3	-0.099	0.119	-0.025	-0.228	-0.385	-0.286	-0.316
	[-0.659]	[3.056]	[-0.349]	[-2.899]	[-2.463]	[-1.52]	[-2.736]
Alpha, FF3+MOM	-0.083	0.137	-0.015	-0.226	-0.366	-0.283	-0.323
	[-0.598]	[2.993]	[-0.198]	[-2.834]	[-2.404]	[-1.52]	[-2.921]

	1 (Low)	2	3	4	5 (High)	High−Low	(4+5)−(1+2)
Panel C: λ^{RT} and the Cross-Section of Stock Returns							
Raw return	0.638	0.77	0.787	0.446	0.295	-0.343	-0.334
	[1.386]	[1.491]	[1.554]	[0.879]	[0.562]	[-1.957]	[-3.323]
Alpha, CAPM	-0.114	0.015	0.067	-0.278	-0.499	-0.385	-0.34
	[-0.523]	[0.103]	[0.569]	[-2.97]	[-1.898]	[-2.309]	[-3.572]
Alpha, FF3	-0.087	0.046	0.103	-0.237	-0.444	-0.357	-0.32
	[-0.587]	[0.94]	[1.639]	[-2.718]	[-3.042]	[-2.044]	[-2.582]
Alpha, FF3+MOM	-0.08	0.068	0.113	-0.235	-0.419	-0.339	-0.321
	[-0.565]	[1.91]	[1.633]	[-2.603]	[-3.066]	[-1.97]	[-2.62]

Table XIII

Fama-MacBeth Regression Results of IV Kurtosis

This table displays Fama-MacBeth regression results of monthly returns on IV Kurtosis (IVKurt) and other control variables. IV Kurtosis (IVKurt) is measured using intraday quartic variations of the log change in IV. Vol-of-Vol (VoV) is the volatility of daily IV scaled by average daily IV of each month. IV Skewness (IVSkew) is measured using intraday cubic variations of the log change in IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. Size is the market capitalization (in $billions). LBM is the log of book-to-market ratio. Reversal is the return of past month t. Momentum is return of past 6 month (from t−6 to t−1). MaxRet is the maximum daily return of past month t. HSkew is the historical skewness computed using past month's daily return. HKurt is the historical kurtosis computed using past month's daily return. OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. OTMSkew is computed as the average of daily difference between the implied volatility of out-of-money puts and the implied volatility of at-the-money calls with around 30-day time-to-maturity. The sample period is from January 2004 to December 2014.

	Model 1	Model 2	Model 3
IVKurt	-0.0002	-0.0001	-0.0001
	[-4.0333]	[-2.2764]	[-2.1428]
VoV		-0.0156	0.0014
		[-1.9164]	[0.1499]
IVSkew		0.0002	-0.0008
		[0.4177]	[-1.0091]
Size			-0.0013
			[-1.8082]
LBM			0.0005
			[0.4256]
Reversal			0.0178
			[0.6955]
Momentum			0.0232
			[1.1108]
MaxRet			0.0089
			[0.2577]
HSkew			-0.0001
			[-0.1162]
HKurt			0.0004
			[1.2887]
OptSpread			0.0011
			[0.2023]
ImpVol			-0.0298
			[-2.971]
OTMSkew			-0.0488
			[-3.391]
Adj. R^2(%)	0.25	0.41	7.01

Table XIV

VTR and Volatility-of-Volatility

This table displays Fama-MacBeth regression results of monthly returns on VTR and Vol-of-Vol (VoV). VTR is the monthly volatility tail risk measure. Vol-of-Vol (VoV) is the volatility of daily IV scaled by average daily IV of each month (See Baltussen et al. (2014)). IVSkew is measured using intraday cubic variations of the log change in IV. IV is calculated as the average implied volatility of a group of at-the-money options with maturity closest to 30 days. Size is the market capitalization (in $billions). LBM is the log of book-to-market ratio. Reversal is the return of past month t. Momentum is return of past 6 month (from t−6 to t−1). MaxRet is the maximum daily return of past month t. HSkew is the historical skewness computed using past month's daily return. HKurt is the historical kurtosis computed using past month's daily return. OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. OTMSkew is computed as the average of daily difference between the implied volatility of out-of-money puts and the implied volatility of at-the-money calls with around 30-day time-to-maturity. The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

Panel A: Fama-MacBeth Regressions of VTR and Vol-of-Vol

	Model 1	Model 2	Model 3	Model 4	Model 5
VTR	-0.0168			-0.0156	-0.0121
	[-3.1203]			[-2.9919]	[-2.7101]
VoV		-0.0198		-0.0153	0.0021
		[-2.729]		[-2.0508]	[0.2252]
IVSkew			0.0006	0.0003	-0.0007
			[1.0388]	[0.642]	[-0.8604]
Size					-0.0015
					[-1.9967]
LBM					0.0005
					[0.4263]
Reversal					0.0155
					[0.6107]
Momentum					0.0209
					[1.0064]
MaxRet					0.0078
					[0.2254]
HSkew					-0.0000
					[-0.0264]
HKurt					0.0004
					[1.3616]
OptSpread					-0.0002
					[-0.0396]
ImpVol					-0.0297
					[-2.9206]
OTMSkew					-0.0476
					[-3.3858]
Adj. R^2(%)	0.37	0.13	0.04	0.51	7.09

This table displays the double-sorting results on VTR and Vol-of-Vol (VoV). VTR is the monthly volatility tail risk measure. Vol-of-Vol (VoV) is the volatility of daily IV scaled by average daily IV of each month (See Baltussen et al. (2014)). The double-sorting methodology is implemented as follows: stocks are first sorted into 5 groups by VoV, then sorted into 5 groups by VTR within each VoV group. Panel B-1 reports raw returns. Panel B-2 reports Carhart (1997) four-factor alphas. The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

Panel B: Double-Sorting of VTR and Vol-of-Vol

Panel B-1: Raw Return

		VTR					
		1 (Low)	2	3	4	5 (High)	High-Low
VoV	1 (Low)	0.009	0.007	0.009	0.006	0.003	-0.006
		[1.838]	[1.558]	[1.727]	[1.121]	[0.536]	[-1.528]
	2	0.006	0.009	0.007	0.005	0.004	-0.002
		[1.524]	[2.095]	[1.352]	[1.118]	[0.859]	[-1.019]
	3	0.005	0.008	0.008	0.005	0.003	-0.002
		[1.306]	[1.621]	[1.354]	[0.839]	[0.465]	[-0.968]
	4	0.006	0.005	0.007	0.006	0.001	-0.005
		[1.163]	[0.884]	[1.356]	[1.226]	[0.175]	[-3.394]
	5 (High)	0.007	0.006	0.007	0.003	0.002	-0.005
		[1.242]	[1.173]	[1.022]	[0.498]	[0.403]	[-1.647]

Panel B-2: Alpha, FF3+MOM

		1 (Low)	2	3	4	5 (High)	High-Low
VoV	1 (Low)	0.002	0.001	0.002	-0.001	-0.004	-0.006
		[1.668]	[0.587]	[2.806]	[-0.493]	[-1.564]	[-2.134]
	2	0.000	0.003	0.000	-0.002	-0.003	-0.002
		[-0.215]	[2.119]	[-0.276]	[-1.768]	[-2.454]	[-0.856]
	3	-0.002	0.001	0.001	-0.002	-0.004	-0.002
		[-0.973]	[0.379]	[0.399]	[-1.007]	[-1.441]	[-0.554]
	4	-0.002	-0.002	0.000	-0.001	-0.006	-0.005
		[-1.628]	[-1.712]	[0.271]	[-0.942]	[-5.820]	[-3.143]
	5 (High)	0.000	-0.001	-0.001	-0.004	-0.005	-0.005
		[-0.016]	[-0.641]	[-0.259]	[-1.713]	[-2.257]	[-1.815]

Table XV

VTR and Stock Volatility

This table reports double-sorting results on VTR and tVol (and iVol) on the purpose of disentangling the volatility tail risk effect from the volatility effect documented by Ang et al. (2006). Specifically, **tVol** represents the total volatility of stock returns. **iVol** represents the idiosyncratic volatility relative to Fama-French 3 factor model defined in Ang et al. (2006). Firms' tVol and iVol are estimated at the end of each month using daily returns. The double-sorting methodology is implemented as follows: stocks are first sorted into 5 groups by tVol (or iVol), then sorted into 5 groups by VTR within each tVol (or iVol) group. The Carhart (1997) four-factor alphas are computed for all portfolios and for all long-short strategies. The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

Panel A: Double-Sorting on VTR and Stock Volatility

		VTR					
		1 (Low)	2	3	4	5 (High)	High-Low
tVol	1 (Low)	0.003	0.004	0.003	0.003	0.003	0.000
		[5.344]	[5.270]	[2.254]	[2.106]	[3.129]	[-0.357]
	2	0.000	0.002	0.001	0.004	0.002	0.002
		[-0.037]	[2.354]	[1.003]	[1.905]	[1.843]	[1.242]
	3	0.000	-0.001	-0.001	0.000	-0.004	-0.004
		[0.001]	[-1.291]	[-0.547]	[0.038]	[-2.175]	[-1.489]
	4	0.000	0.000	-0.001	-0.002	-0.005	-0.006
		[0.103]	[-0.099]	[-0.719]	[-1.020]	[-3.647]	[-1.937]
	5 (High)	-0.006	-0.002	-0.007	-0.009	-0.013	-0.007
		[-3.187]	[-0.977]	[-3.872]	[-2.525]	[-3.261]	[-1.917]
iVol	1 (Low)	0.002	0.003	0.004	0.003	0.003	0.002
		[1.877]	[5.021]	[4.854]	[2.495]	[4.600]	[1.132]
	2	0.001	0.003	0.002	0.000	0.000	-0.001
		[1.057]	[3.795]	[2.819]	[0.014]	[0.284]	[-0.385]
	3	-0.002	0.000	0.000	-0.001	-0.002	0.000
		[-1.048]	[-0.328]	[-0.020]	[-1.116]	[-1.516]	[-0.069]
	4	-0.001	-0.001	-0.001	0.000	-0.006	-0.005
		[-0.388]	[-1.158]	[-0.376]	[-0.026]	[-3.272]	[-1.750]
	5 (High)	-0.006	-0.002	-0.007	-0.009	-0.012	-0.006
		[-4.321]	[-0.984]	[-4.352]	[-2.487]	[-2.979]	[-1.723]

This table reports Fama-MacBeth regression results of monthly returns on VTR and stock volatility measures (tVol and iVol). VTR is the monthly volatility tail risk measure. Size is the market capitalization (in $billions). LBM is the log of book-to-market ratio. Reversal is the return of past month t. Momentum is return of past 6 month (from t−6 to t−1). MaxRet is the maximum daily return of past month t. HSkew is the historical skewness computed using past month's daily return. HKurt is the historical kurtosis computed using past month's daily return. OptSpread is the average option spread of at-the-money options. ImpVol is the average implied volatility of at-the-money calls with around 30-day time-to-maturity. OTMSkew is computed as the average of daily difference between the implied volatility of out-of-money puts and the implied volatility of at-the-money calls with around 30-day time-to-maturity. O/S is the option-to-stock volume ratio measured at monthly frequency. The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

Panel B: Fama-MacBeth Regressions on VTR and Stock Volatility

	Model 1	Model 2	Model 3
VTR	-0.0122	-0.0123	-0.0122
	[-2.7055]	[-2.7731]	[-2.6781]
tVol		-0.2046	
		[-1.3153]	
iVol			-0.1724
			[-1.212]
Size	-0.0014	-0.0014	-0.0014
	[-1.9528]	[-1.9623]	[-1.9175]
LBM	0.0004	0.0005	0.0004
	[0.3477]	[0.3949]	[0.3176]
Reversal	0.0156	0.0155	0.0186
	[0.6233]	[0.6377]	[0.7349]
Momentum	0.0211	0.0257	0.0259
	[0.9827]	[1.103]	[1.1179]
MaxRet	0.0148	0.0766	0.0561
	[0.4269]	[2.227]	[1.1158]
HSkew	-0.0001	-0.0013	-0.0006
	[-0.2255]	[-1.7585]	[-1.1631]
HKurt	0.0004	0.0003	0.0004
	[1.3239]	[1.2974]	[1.5323]
OptSpread	-0.0006	-0.0003	-0.0001
	[-0.1744]	[-0.0953]	[-0.0275]
ImpVol	-0.0296	-0.0258	-0.0265
	[-3.0237]	[-2.9071]	[-3.0322]
OTMSkew	-0.0525	-0.0528	-0.0507
	[-3.8472]	[-3.8681]	[-3.6985]
O/S	0.0019	0.002	0.002
	[0.6792]	[0.7148]	[0.7018]
Adj. R^2(%)	7.08	7.32	7.33

Table XVI

Double-Sorting on VTR and Firm Size

This table displays the double-sorting results on VTR and firm size. VTR is the monthly volatility tail risk measure. Size is the market capitalization (in $billions). The double-sorting methodology is implemented as follows: stocks are first sorted into 5 groups by Size, then sorted into 5 groups by VTR within each Size group. Panel A reports raw returns. Panel B reports Carhart (1997) four-factor alphas. The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

		VTR					
		1 (Low)	2	3	4	5 (High)	High-Low
Panel A: Raw Return							
Size	1 (Low)	0.007	0.004	0.003	0.002	-0.004	-0.011
		[1.363]	[0.706]	[0.558]	[0.338]	[-0.863]	[-3.178]
	2	0.006	0.007	0.005	0.005	0.004	-0.001
		[1.234]	[1.233]	[1.011]	[0.851]	[0.876]	[-0.650]
	3	0.009	0.008	0.008	0.007	0.007	-0.002
		[1.646]	[1.804]	[1.495]	[1.208]	[1.181]	[-0.684]
	4	0.008	0.009	0.009	0.007	0.006	-0.002
		[1.502]	[1.749]	[1.662]	[1.081]	[0.935]	[-0.505]
	5 (High)	0.006	0.007	0.006	0.008	0.006	0.000
		[1.415]	[1.436]	[1.384]	[1.594]	[1.159]	[0.055]
Panel B: Alpha, FF3+MOM							
Size	1 (Low)	-0.001	-0.004	-0.004	-0.006	-0.012	-0.011
		[-0.632]	[-2.634]	[-2.179]	[-3.345]	[-2.970]	[-3.237]
	2	-0.002	0.000	-0.002	-0.003	-0.003	-0.001
		[-1.038]	[0.064]	[-1.401]	[-1.233]	[-2.104]	[-0.480]
	3	0.001	0.001	0.001	0.000	0.000	-0.001
		[0.904]	[1.076]	[0.725]	[-0.006]	[0.114]	[-0.499]
	4	0.000	0.002	0.002	0.000	0.000	-0.001
		[0.094]	[1.500]	[1.641]	[0.125]	[-0.149]	[-0.151]
	5 (High)	-0.001	0.001	0.000	0.002	0.001	0.001
		[-0.496]	[1.091]	[0.096]	[2.347]	[0.363]	[0.451]

Table XVII

Double-Sorting on VTR and Option Characteristics

This table displays the double-sorting results on VTR and option characteristics. VTR is the monthly volatility tail risk measure. OptSpread is the average option quote spread of at-the-money 30-day options, a proxy for information asymmetry in microstructure literature. OptVolume is the total option trading volume, a measure of option liquidity. The double-sorting methodology is implemented as follows: stocks are first sorted into 5 groups by OptSpread (OptVolume), then sorted into 5 groups by VTR within each OptSpread (OptVolume) group. The Carhart (1997) four-factor alphas are reported for all portfolios and for all long-short strategies. The Newey-West (1987) t-statistics are reported in square brackets. The sample period is from January 2004 to December 2014.

Double-Sorting on VTR and Option Characteristics

		VTR					
		1 (Low)	2	3	4	5 (High)	High-Low
OptSpread	1 (Low)	-0.003	-0.001	-0.001	-0.001	-0.002	0.001
		[-1.101]	[-0.421]	[-0.988]	[-0.927]	[-1.069]	[0.425]
	2	0.002	0.000	0.001	0.002	-0.007	-0.008
		[0.711]	[-0.099]	[0.555]	[1.032]	[-3.412]	[-2.492]
	3	0.003	-0.001	0.000	0.000	-0.007	-0.010
		[1.772]	[-1.009]	[-0.006]	[-0.387]	[-2.775]	[-3.283]
	4	0.001	0.000	-0.001	-0.005	-0.007	-0.008
		[0.595]	[0.112]	[-0.784]	[-4.353]	[-3.683]	[-3.290]
	5 (High)	0.002	0.000	0.001	-0.002	-0.003	-0.005
		[1.238]	[0.312]	[0.515]	[-1.135]	[-1.306]	[-2.142]
OptVolume	1 (Low)	0.001	0.003	0.001	-0.001	-0.001	-0.002
		[0.719]	[2.467]	[0.478]	[-0.391]	[-0.485]	[-0.787]
	2	0.003	0.000	0.001	-0.001	-0.004	-0.007
		[2.017]	[-0.371]	[0.633]	[-0.676]	[-2.094]	[-3.560]
	3	0.002	0.001	0.002	-0.001	-0.008	-0.010
		[1.056]	[1.262]	[2.009]	[-1.035]	[-4.389]	[-4.905]
	4	0.000	0.001	0.000	-0.004	-0.006	-0.007
		[0.219]	[0.604]	[-0.254]	[-2.579]	[-3.122]	[-2.405]
	5 (High)	-0.003	-0.003	-0.002	-0.003	-0.007	-0.004
		[-1.147]	[-2.910]	[-1.863]	[-1.928]	[-4.203]	[-1.159]

Why Do Option Returns Change Sign from Day to Night? *

Dmitriy Muravyev and Xuechuan Ni[a]

Abstract

Average returns for S&P 500 index options are negative and large: -0.7% per day. Strikingly, when we decompose these delta-hedged option returns into intraday (open-to-close) and overnight (close-to-open) components, we find that average overnight returns are -1%, while intraday returns are actually positive, 0.3% per day. A similar return pattern holds for all maturity and moneyness categories, and equity options. Rational theories struggle to explain positive intraday returns. However, our results are consistent with option prices failing to account for the well-known fact that stock volatility is substantially higher intraday than overnight. These results help us better understand the price formation in the options market.

JEL Classification: G12, G13, G14

Keywords: Option returns, volatility seasonality, behavioral finance

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Abstract

Average returns for S&P 500 index options are negative and large: -0.7% per day. Strikingly, when we decompose these delta-hedged option returns into intraday (open-to-close) and overnight (close-to-open) components, we find that average overnight returns are -1%, while intraday returns are actually positive, 0.3% per day. A similar return pattern holds for all maturity and moneyness categories, and equity options. Rational theories struggle to explain positive intraday returns. However, our results are consistent with option prices failing to account for the well-known fact that stock volatility is substantially higher intraday than overnight. These results help us better understand the price formation in the options market.

JEL Classification: G12, G13, G14

1 Introduction

Derivatives play an important role in the economy. They help to complete the market and allow for a capital-efficient hedging and speculation. However, policymakers are concerned that because derivatives are so complex, even professional investors may not fully understand their risks and even occasionally misprice them. We find evidence consistent with this concern in one of the world's most widely-studied, actively-traded, and transparent derivatives markets – the options market.[1] Based on these characteristics, one would expect option prices to be efficient and fair. Yet, we find that option prices are systematically biased, and positive intraday option returns are particularly hard to explain. Our results are consistent with option prices failing to account for a well-known volatility seasonality – volatility is usually higher during trading hours than overnight. This conclusion is notable because volatility is obviously a major input to option pricing models, and the models can be easily adjusted for the volatility seasonality. Perhaps, prices in other derivatives markets may similarly deviate from their fair values preventing efficient capital allocation.

To understand our main result, let us first explain the intuition behind *average* option returns. In the Black-Scholes-Merton (BSM) model, an option can be perfectly replicated by hedging continuously in the underlying stock. Thus, a delta-hedged option portfolio earns a risk-free rate of return. However, average delta-hedged option returns are negative in practice, implying that option sellers collect a risk premium from option buyers. Average delta-hedged option returns are also directly related to the variance risk premium – option-implied variance exceeds the realized return variance on average. Although option returns have been extensively studied,[2] there is an active debate about whether these large negative returns reflect compensation for taking risk or due to mispricing.[3] Numerous studies show that option investors are highly sophisticated, which makes mispricing less likely.

We contribute to this debate by documenting a remarkable pattern in *average* delta-hedged option returns. In particular, option returns are only negative during the

[1] Indeed, according to Option Clearing Corporation, U.S. equity options had a notional volume of 372 trillion shares in 2015, which is about one-fifth of trading volume in U.S. equities.
[2] E.g., Bakshi and Kapadia (2003), Carr and Wu (2009), and Bakshi, Madan, and Panayotov (2010).
[3] For example, Han (2008) and Bondarenko (2014) advocate the mispricing and sentiment explanations.

overnight period (from close to open) and are mildly positive intraday (open-to-close). Overnight delta-hedged returns are -1.0% per day for index options and -0.4% for equity options and are notably persistent over our sample period from 2004 to 2013. In contrast, during the trading day, option returns flip sign and become positive: 0.3% per day for index options and 0.1% for equity options. This day-night effect is stronger for options with high-embedded leverage, such as short-term and out-of-the-money options. VIX futures returns show a similar, albeit weaker, pattern. Importantly, this option return asymmetry varies across stocks and ETFs. For most ETFs and stocks, option returns are positive intraday but for some the pattern is reversed with positive returns overnight.

This day-night effect is not only puzzling in itself but it also makes harder to rationalize why average option returns are so negative. Indeed, literature struggles to explain why returns for selling a delta-hedged option on the S&P 500 index are so positive, 0.7% per day in our sample.[4] A common justification is that this trading strategy is akin to “picking up nickels in front of a steamroller” and lost 80% of its capital during the financial crisis. However, as option returns are only negative overnight, this baseline strategy can be improved by only selling option volatility overnight, with no position during the day. The overnight strategy not only increases average returns to 1.0%, but also more than doubles its Sharpe ratio. Moreover, it is profitable in every three-month period, including the crisis! Thus, it poses new challenges for rational option theories. Admittedly, large trading costs in index options make this trading strategy hard to implement in practice. However, the strategy is potentially profitable after costs in important special cases, such as options on the most popular index ETF, SPY.

We consider a number of potential risk and friction-based explanations for the striking asymmetry between day and night returns, including stochastic volatility and price jumps, inability to adjust delta-hedge overnight, price pressure, discretization error, transaction costs, funding and other carry costs. The proposed theories should explain not only the return asymmetry but also its cross-asset variation. Although, most of these theories are consistent with some of the facts and help explain negative night returns, most of them struggle with positive intraday returns, and even zero returns would be

[4] These estimates are consistent with the prior literature that uses older data Coval and Shumway (2001), Bakshi and Kapadia (2003), Santa-Clara and Saretto (2007), and Broadie, Chernov, and Johannes (2009).

puzzling. Simply put, why would put options, which provide insurance against market crashes, offer positive average returns? For example, if our sample period missed an intraday rare disaster, this "peso problem" would worsen the intraday return puzzle. A disaster would trigger large positive returns for a delta-hedged option, and thus the "true" average return is even more positive than our estimate. Another natural explanation is that option investors consider night particularly risky due to the inability to adjust delta-hedges and option positions. Therefore, investors require larger compensation for bearing volatility risk during night, and thus overnight option returns should be particularly negative. This theory implies *less negative* intraday returns, but the returns are positive. Adding to the challenge, negative overnight returns do not depend on volatility (such as VIX) and measures of tail risk. In contrast, most rational theories predict that expected option returns should depend on market conditions. Finally, rational theories struggle to explain the cross-stock variation in day-night option returns.

On a more positive note, price pressure and the "discretization bias" likely contribute to positive intraday returns. Order imbalances for index options are positive and may push option prices higher causing positive intraday returns. However, the imbalances are not large, and in theory, such anticipated imbalances should be reflected in prices in advance. Branger and Schlag (2008) introduce the discretization bias and argue that infrequent delta-hedging and biased option deltas may lead to positive option returns. We conduct several tests that reduce but not completely eliminate this concern. Finally, conventional jump and stochastic volatility theories are promising if option investors love taking intraday risk. Obviously, high option trading costs limit the ability of arbitrageurs to eliminate the day-night effect; however, the costs cannot explain why this effect exists in the first place. We further discuss all the explanations in Section 5.1.

The limited success of rational theories in explaining the day-night effect implies that option market-makers (OMMs) may not be fully rational, in the sense that they post systematically biased prices. Instead of settling on this "residual" conclusion, we propose and test a simple behavioral explanation. Perhaps, option returns change sign from negative overnight to positive intraday because option prices fail to account for the fact that stock volatility is on average much higher intraday than overnight. This well-known fact is perhaps the strongest volatility seasonality.[5] We document its properties for individual stocks and S&P 500 index in our sample. Surprisingly, option prices are set as if total intraday and night volatilities were about the same, totally ignoring the seasonality. This failure to account for the volatility seasonality translates into option returns. Indeed, option delta-hedged returns are proportional to the difference between realized and implied volatilities (Bakshi and Kapadia, 2003). Implied volatility is usually set slightly above the expected realized volatility resulting in negative average option returns, which compensates investors for taking volatility/tail risks. Therefore, positive intraday (negative night) returns imply that option prices understate intraday (overstate overnight) volatility. Option close prices are too high, and open prices are too low. Admittedly, the effect on implied volatility is less dramatic as it reflects total remaining variance until expiration with about the same number of day and night periods.

We conduct two major tests to further validate the volatility bias hypothesis. First, it predicts that stocks with more pronounced day-night volatility seasonality should have higher day-night asymmetry in option returns. That is, if options are priced assuming the same volatility for day and night, while actual volatility is much higher intraday, then intraday option returns will be more positive (and night return more negative). We test this prediction with portfolio sorts and regressions on a cross-section of more than thousand optionable stocks. Remarkably, the day-to-night volatility ratio computed from historical data explains most of the variation in the day-night option return asymmetry across stocks and thus helps resolve the day-night puzzle. Also, both day and night option returns become negative after accounting for the volatility seasonality bias. That is, returns seem consistent with conventional theories after accounting for the bias.

In the second test, we add the day-night volatility seasonality to the standard Black-Scholes and Heston models. In the model, we control for how much option prices underreact to the volatility seasonality and thus can study the volatility bias in controlled settings. Specifically, options are priced using a different day-night volatility ratio than the actual ratio that generates the underlying stock price. We simulate day-night option returns from both models under realistic parameter values. First, the models are able to replicate not only signs but also magnitudes of day-night option return if option prices

[5] Oldfield and Rogalski (1980), Amihud and Mendelson (1991), Stoll and Whaley (1990) among others.

completely ignore the day-night volatility seasonality. That is, options' prices seem not simply underreact but completely ignore the volatility seasonality. Second, day-night option returns depend primarily on perceived volatility ratio reflected in option prices and much less on the actual volatility ratio. We also confirm our cross-stock results, as we find similar regression results in a simulated panel of option returns from the BSM model. It is reassuring that both models produce similar results.

Interestingly, other option investors do not seem to take advantage of the day-night effect. Many investors could be simply unaware of it. Positive intraday returns encourage option investors to move their sell (buy) trades to the afternoon (morning). Contrary to this prediction, option order imbalance is more positive in the afternoon; that is, investors buy more (and thus sell fewer) options towards close.

We conduct numerous robustness tests. Our main results are robust to alternative definitions of open and close prices (e.g., using trade prices instead of quote midpoints), option returns (e.g., using leverage-adjusted, straddle, and raw returns), and different subsamples (e.g., for all of the moneyness and time-to-expiration categories).

Empirical work in option pricing typically relies on the estimation of fully specified parametric models. Option returns are easier to interpret than the pricing errors of such models because returns represent the actual gains or losses to a trading strategy. Also, the day-night effect is hard to extract from implied volatility, and thus option returns provide a more natural way to study them. Several others have also noted the advantages of analyzing average option returns.[6]

Overall, multiple explanations likely contribute to the day-night effect, but the volatility bias is by far the most promising. The remainder of the paper is organized as follows. In Section 2, we briefly review the related literature. In Section 3, we describe the data and the methodology. Section 4 documents the asymmetry between day and night option returns, while Section 5 tries to explain it. Section 6 concludes the paper. The Appendix provides several additional results and tables.

[6] See for example Coval and Shumway (2001), Bondarenko (2003), Driessen, Maenhout, and Vilkov (2009), Duarte and Jones (2007), Broadie, Chernov, and Johannes (2009), Goyal and Saretto (2009), Bakshi, Madan, and Panayotov (2010), and Muravyev (2016).

2 Literature and Contribution

This paper contributes to several strands of literature. First, our results are obviously important for the option returns literature. Second, we contribute to the literature that studies behavioral finance and investor irrationality. Although options provide leverage (Black, 1975) and lottery-like payoffs (Shefrin and Statman, 1993) that can attract speculators, some of whom may act irrationally, surprisingly few papers including study behavioral factors in derivatives markets. Stein (1989) and Poteshman (2001) show that option-implied volatility underreacts to individual daily changes in instantaneous variance and overreacts to periods of mostly increasing or mostly decreasing daily changes in variance. Han (2008) shows that changes in investor sentiment help explain time variation in the slope of index option smile and risk-neutral skewness. Jones and Shemesh (2016) show that returns for stock options are more negative over weekends than weekdays. Overall, these studies argue that the option market reacts in the right direction but the magnitudes are too large, while we find that intraday option return have a “wrong” sign and identify a likely mechanism behind the puzzle. Relatedly, the literature on the optimal exercise of equity options concludes that professional investors, such as OMMs, almost always exercise their options optimally while retail investors occasionally make mistakes, which is hardly surprising because optimal exercise boundaries are hard to compute. This paper focuses on systematic pricing mistakes by market-makers rather than occasional mistakes by retail investors.

We know only one other paper, Sheikh and Ronn (1994), that investigates intraday patterns in option returns. Using the data on short-term at-the-money options on 30 stocks for just 21 months ending pre the 1987 crisis (pre volatility skew period), they find, among other results, that “the adjusted option returns” are more negative overnight than intraday but the difference is not statistically significant, perhaps because their sample is too small. Sheikh and Ronn focus on returns towards the end of trading day, and do not discuss overnight versus intraday returns, nor do they study index options. They argue that differences between option and equity market returns provide evidence of information-based trading in options. Obviously, the options market has changed substantially since mid-1980s. Also, Chan, Chung, and Johnson (1995) show that option volume exhibits a U-shaped intraday pattern similar to stock volume; however, we are the first to examine intraday patterns in option order flow/imbalance.

If OMMs ignore the day-night volatility, this is extremely puzzling because volatility is a major input to option pricing models, and these models can be easily adjusted for the volatility seasonality.[7] The idea that volatility seasonality should affect option prices goes back to at least Merton (1973) and French (1984). Also, option investors are highly sophisticated, which makes mispricing less likely: institutional investors account for most of option trading volume.[8] Indeed, numerous studies show that option prices and volume contain information about future unscheduled events (e.g., mergers), stock returns, and volatility.

A growing literature examines the day-night effect in equity returns.[9] Our result that option investors potentially misprice the day-night volatility can potentially be useful for explaining the equity market day-night puzzles. Volatility is a basic input to many risk measures such as CAPM betas and thus may affect required rate of return for night and day. Importantly, despite apparent similarity, the day-night effect in the equity market does not affect our results. First, options are delta-hedged so that their beta is close to zero, and thus option returns are uncorrelated with returns for the underlying. Controlling for stock/index returns does not affect the option day-night effect. Second, unlike in the equity market, the autocorrelation between day and night returns is essentially zero in options. Finally, the options day-night effect is an order of magnitude larger than its equity market counterpart; the latter amounts to only less than one basis point per day in our sample.

The fact that OMMs may ignore short-term swings in the underlying volatility, such as the day-night volatility seasonality, suggests that results of event studies that rely on intraday option data should be interpreted with caution. For example, positive option returns immediately after an intraday announcement, such as macro news, may indicate a

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[7] Option market-making is highly concentrated. According to Citadel, as of late 2008, Citadel (30% of option volume, specialist in options on 1,655 stock names), Susquehanna (1,152 stock names), Timber Hill (1,124), Citi (554), Goldman Sachs (390), Morgan Stanley (286), UBS (218) dominated this market.

[8] Muravyev and Pearson (2015) show that most option trades are executed using sophisticated algorithms not available to retail inventors.

[9] For example, Lockwood and Linn (1990) and more recently Cooper, Cliff, and Gulen (2008) show that all of the equity risk premium in their sample comes from overnight returns. Lou, Polk, and Skouras (2015) and Bogousslavsky (2016) examine how stock anomalies behave intraday/overnight.

risk premium associated with this event or, alternatively, OMMs simply ignored the event. In the latter case, option returns will also be positive because they are proportional to the difference between realized volatility, which is high after the announcement, and implied volatility, which is unchanged if the event is ignored.

3 Data and Methodology

We obtained stock and options data from Nanex, a firm specializing in high-quality data feeds. The original data come from standard data aggregators: OPRA for options and SIP for equities (e.g., TAQ data also use SIP). The data include intraday quoted bid and ask prices at one-minute frequency for both options and the underlying equities for the sample period from January 2004 to April 2013. For options, we also observe best bid and offer (BBO) from all option exchanges. Timestamps are synchronized across markets. To reduce dataset size, only option contracts with at least one trade on a given day are included. Still, the compressed data require more than twelve terabytes of storage. When needed, we merge our intraday data with daily stock and option prices from CRSP and OptionMetrics by ticker and date. Delta-hedges are computed using S&P 500 index futures data. Option order imbalances are computed from option trades and BBO quoted prices preceding them. First, the quote rule is applied to trade and NBBO (National Best Bid and Offer) to determine whether a trade is buyer or seller-initiated; if a trade is at the NBBO quote midpoint, we apply the quote rule to the quoted bid and ask prices from the exchange that reported the trade.

Let us briefly describe the options market structure. The U.S. options market has a similar structure to the equity market with some distinct features. Equity options are typically cross-listed across multiple fully-electronic exchanges, and NBBO rule is enforced. Investors can post limit or market orders, and market-makers are obliged to provide continuous two-sided quotes. All major brokers provide real-time option prices to their (retail) clients similarly to stock information. S&P500 index options are special because one exchange, CBOE, has exclusive rights to trade SPX options, and a lot of trading is still done manually. OMMs provide continuous bid and ask quotes for SPX options that investors can trade against. Johnson, Liang, and Liu (2016) and Muravyev (2016) provide further details.

Open price is computed as the quote midpoint at 9:40 a.m. We skip the first ten minutes of trading (both the equity and options markets open at 9:30 a.m. EST) because, as Chan, Chung, and Johnson (1995) first show and we confirm, option quotes are sporadic and bid-ask spreads are often wide right after market opens. Closing prices are based on the quote midpoint preceding close, which is 4:00 p.m. for equity and 4:15 p.m. for S&P options. Options and the underlying market typically close/open at the same time. Our main results are robust to alternative specifications of open and close prices.

We apply standard data filters. In order to compute option return over a given time period, we exclude option contracts for which at the beginning of this period (1) option prices violate no-arbitrage bounds, (2) the bid price is greater or equal to the ask price, (3) the bid price is not available or is below 50 cents, (4) the quoted bid-ask spread is more than 70% of the midpoint or three dollars, or (5) if option delta cannot be computed. Omitting any one of these filters has little effect on our main results.

Delta-hedged option returns are computed using deltas from the Black-Scholes-Merton model; and the hedge is revised five times a day (approximately every 80 minutes). Figure A.2 in the Appendix confirms that our main results are robust to alternative hedging frequencies. Following the literature, we define delta-hedged option dollar profit (P&L) for option contract with price C_t between times $t-1$ and t as

$$P\&L_t = C_t - C_{t-1} - \Delta_{t-1} * (S_t - S_{t-1}) \,,$$

where Δ is option delta and S_t is the underlying price at time t. Option delta-hedged return is then computed as[10]

$$Ret_t = \frac{P\&L_t}{C_{t-1}}$$

Following this definition, intraday (open-to-close) returns are computed as the intraday (open-to-close) dollar P&L for a long option position divided by opening option price. Index futures have low margin costs supporting this definition. In untabulated results, we show that other ways to normalize P&L (instead of simply dividing by option price) expectedly affect the magnitudes of day- night option returns but not their signs.

We first compute day and night returns for each option contract, then average them for each underlying, and finally take an equally-weighted average across stocks

[10] We study regular option returns instead of excess returns because daily risk-free rate is negligible compared to option returns, and thus, subtracting it makes little difference.

(this step is not needed for S&P index options). Thus, this gives us one intraday and one overnight return per stock and date. With slightly less than ten years of data, we end up with more than 2200 daily observations. When required, we similarly compute returns for option subsamples such as out-of-the-money (OTM) index puts.

For robustness, we also examine leverage-adjusted option returns, which help us compare returns of options with different moneyness. Following the literature, the deleveraged option return for Ret_t is defined as:

$$Ret_t^{DL} = \frac{Ret_t}{\psi_{t-1}}, where\ \psi_{t-1} = \left|\frac{\Delta_{t-1}S_{t-1}}{C_{t-1}}\right|,$$

Ret_t is the delta-hedged option return for time period $[t-1, t]$ defined above. ψ_{t-1} is the deleveraged factor. The deleveraged factor, ψ, is usually well above 5.

It is also important to clarify why we study option returns and not just open and close VIX levels or other implied volatility measures (including "model-free" versions). VIX alone tells us little about whether option prices are cheap or expensive. It is mechanically higher at open and lower at close (and also higher on Monday and lower on Friday) because it is computed based on calendar instead of business time, which is another manifestation of the volatility seasonality bias. Whether option prices are cheap/expensive is jointly determined by implied and realized volatilities, and option returns is a convenient way to access this.

4 The Day-and-Night Effect in Option Returns

4.1. Average Overnight and Intraday Option Returns

In this section, we explore properties of average overnight and intraday option returns. Figure 1 shows our main result. We decompose daily delta-hedged option returns into intraday (open-to-close) and overnight (close-to-open) components. It is well known that delta-hedge returns for index options (and to a lesser degree for equity options) are negative on average. We show that these negative returns are entirely due to the returns from the overnight period, which are -1.0% per day, while intraday returns are positive (0.3%). Our magnitudes for total daily option returns are consistent with the literature (e.g., Coval and Shumway, 2001). Tables 1 and 3 confirm that day and night returns are both statistically significant (t-statistics of 2.6 and -12 respectively). This day-night effect is also observed in equity option returns, but magnitudes are expectedly smaller: a -0.4% per day overnight return and 0.1% intraday (see Figure 1, Table 1 Panel B, and Table A.2 in the Appendix). Statistical significance is higher for equity options (t-statistics of -19 and 3) as averaging across stocks reduces estimation error.

Figure 2 shows that despite high variance, overnight returns are remarkably stable over the entire sample period. In particular, this figure compares cumulative option returns over a three-month rolling window for two trading strategies. The conventional strategy of collecting the option risk premium sells a delta-hedged option portfolio and keeps it for the entire day (thus collecting both day and night returns) while the "overnight" strategy only keeps the short position open overnight and thus has no position intraday. The conventional strategy is highly profitable but the P&L is highly volatile, and it loses more than 80% of capital in late 2008. In contrast, the overnight strategy is profitable in every three-month sub-period, including the crisis. As a result, it yields more than twice the Sharpe ratio of the conventional strategy. Admittedly, the overnight strategy is hard to implement in practice as it requires frequent trading. Its average daily profits are smaller than a 6% average effective bid-ask spread in S&P500 index options. Of course, investors do not need to pay the entire spread and can also provide liquidity. In Section 5.6, we discuss how options on SPY ETF, which have similar return properties but much smaller transactions costs, can be used to make the overnight strategy potentially profitable after costs. Importantly, high trading costs can explain why the anomaly does not disappear, but not why it exists in the first place.

Table 4 complements this analysis by reporting option returns by calendar year. First, both night returns as well as the difference between day and night returns are economically and statistically significant in every year of our sample. The least negative night returns are -0.77% in 2008. The smallest day-night difference is 0.89% in 2012. Second, the intraday returns are quite volatile and are positive or close to zero in all years. The most negative intraday return is -0.21% in 2012 (t-statistics of -0.8). Overall, day-night option return asymmetry is observed in every year.

The day-night return difference cannot be explained by differences in higher moments of option return distribution. Table 1 shows that day and night option returns have about the same volatility of 4.8% and similar 1% and 99% tail quantiles. Thus, at least in terms of these "naïve" risk measures day and night returns are similarly risky.[11]

To better understand the nature of intraday returns, we compute average option returns over five equal intraday sub-periods in Table 3. The intraday returns are close to zero in the morning and noon (-0.02%) and become positive in the afternoon and especially before close (0.16% and 0.19% in the last two sub-periods). Interestingly, index option returns have a different intraday pattern than the underlying volatility, which has a pronounced U-shape: volatility is highest at the open and close. However, equity option returns are more positive during the beginning (0.10%) and end (0.05%) of the trading day (vs. -0.04% during lunch, see Table A.2 in the Appendix) and thus match the U-shape volatility seasonality. Perhaps, we just do not have enough statistical power to find the U-shape in index option returns. Overall, the fact that returns are non-negative for all intraday sub-periods confirms that our results are not driven by some strange price behavior at open or close.

We conduct many other tests and find that our main result is remarkably robust. Sections A.1 and A.2 in the Appendix explain them in detail.[12] In particular, we consider several alternatives for open/close option prices and returns. All of them have little effect on the day-night return magnitudes. First, to elevate concern that we compute open and close prices at a particular time (9:40am and 4pm), we re-compute them as an average quoted price during the first and last 15 minutes of a trading day. Second, to elevate the concern that bid prices can occasionally be set too low and thus bias the midpoint, we compute returns using only ask (or only bid) prices (Table A.9). Third, despite being widely used the quote midpoints may not represent prices that investors get. To address this, we compute option returns from average trade prices instead of quote midpoints (Panel B of Table A.8). If anything the day-night return asymmetry is stronger here.

[11] Expectedly, the median return is lower than the mean because an option payoff is non-linear. Overnight return median is -1.2%, and thus our main result is not driven by outliers. Median intraday return is slightly negative (-0.38%) reflecting the fact that a buyer of an option straddle (put plus call) lose money on a median day because stock price remains unchanged in this median scenario, and thus an option buyer loses time value.

[12] We also confirm in Table 3 that negative overnight returns are not driven by weekends. Night returns become slightly less negative, increasing from -1.0% to -0.8% if weekends are excluded. We thus confirm the finding of Jones and Shemesh (2016) that option returns are more negative over weekends (Friday to Monday). In untabulated results, we also test whether the volatility seasonality bias that we propose can explain the weekend effect, and it does not. Unfortunately, the weekend effect remains a puzzle.

Fourth, hedging in the underlying may produce spurious returns, we study straddle returns to address this concern (Panel A of Table A.7). In a straddle, a call is delta-hedged with corresponding put options instead of the underlying. Finally, delta hedging may affect option returns, e.g. because option deltas can be biased. In Figure A.2, we show that intraday returns depend little on the delta-hedging frequency. Moreover, in Panel B of Table A.7, we confirm the day-night effect for raw (unhedged) option returns.

After documenting the day-night effect in index and equity options, we investigate major exchange-traded funds including U.S. index, industry, commodity, fixed-income, and international equity ETFs (Table A.1).[13] The day-night effect varies across ETFs in a systematic way that matches the pattern in day-night ETF return volatility. Average option returns for U.S. index, industry, and commodity ETFs are negative overnight and positive intraday. However, option returns for international ETFs (e.g., tickers EEM and EFA) and long-term Treasury bond ETF (ticker TLT) are negative in both intraday and overnight. Interestingly, the day-night effect flips sign for the China Large-Cap ETF: night returns are positive, and day returns are negative. These “exceptions” encouraged us to compare average option returns with the day/night return volatility for these ETFs. For the Chinese ETF, intraday volatility is less than overnight volatility; for international equity ETFs and fixed-income ETF, the day and night volatilities are roughly equal. Finally, for U.S. index and industry ETFs, intraday volatility is significantly higher than overnight volatility. Remarkably, the volatility pattern matches the pattern in average option returns! Overall, the variation in day-night option returns across ETFs is an important stylized fact that helps us distinguish between alternative explanations.

Finally, we compare day and night return distributions for the *underlying*. Panels A and B of Table 2 report return distributions for S&P500 index and individual stocks respectively. Average S&P index returns are close to zero during our sample period:

[13] We also find evidence of the day-night effect in VIX futures. In Table A.10, we show that intraday returns for front-month VIX futures are close to zero (0.01%, statistically insignificant) while overnight returns are significantly negative (-0.15%). As VIX futures are traded around the clock but are highly illiquid outside of normal trading hours, we use the same open and close times as for index options to compute VIX futures returns. All futures with maturities up to six months have negative overnight returns and slightly positive (or zero) intraday returns. After launching in 2004, the market for VIX futures really took off only recently, which made futures prices volatile in the beginning of our sample. This may explain the relatively large standard errors.

0.008% for overnight period and -0.004% for intraday. That is, the difference is only one basis point and is not statistically significant. As for the higher moments, intraday period is only 6.5 hours (regular trading hours) but its total volatility is 1.5 times higher than for the longer overnight period. Similarly, return percentiles are more extreme for intraday returns. Excess kurtosis is similar for two return distributions while skewness is significantly more negative for intraday returns. Summary statistics for equity returns are similar to index returns except the magnitudes are more extreme. We first compute statistics for each stock and then report the cross-stock average. For an average stock, overnight returns are higher than intraday by 0.06%. Day and night volatilities are 3.1% and 2.1% respectively. Skewness is positive, particularly overnight.

4.2. Conditional Properties of Option Returns

In this section, we show how day-night option returns depend on option parameters. Overall, the day-night return asymmetry is observed for almost all option subsets that we considered. Table 1 shows that the return asymmetry becomes more pronounced as option moneyness decreases. E.g., OTM options have highest leverage and thus more extreme returns: 0.27% intraday and -1.74% overnight; while in-the-money (ITM) options have little leverage/optionality with day and night returns of only 0.07% and -0.22%. Delta-hedged call and put returns are similar because both produce a similar straddle position after delta-hedging. Finally, Panel B of Table 1 confirms these stylized facts for equity options, but the magnitudes are expectedly smaller.

The return asymmetry declines with time-to-expiration; that is, short-term options have more extreme returns. Table A.4 in the Appendix shows that options with less than three weeks to expiration have average night and day returns of -2.6% and 0.7%, while returns for long-term options are close to zero. Returns for equity options show a similar pattern. Table 5 double-sorts options based on maturity and moneyness and shows that the day-night effect is more pronounced for short-term and more OTM options. ITM long-term options have both returns close to zero, while short-term OTM options have night returns of -5.3% and day returns 0.75%. Relatedly, we also explore how delta-hedged index option returns depend on option Greeks. Table A.5 double-sorts options by normalized option Theta and Vega (option price sensitivity to time-to-expiration and volatility respectively) from the BSM model. The option return asymmetry is decreasing in Theta and increasing in Vega, with the high-Vega low-Theta portfolio having day-night returns of 0.4% and -2%. Day returns are positive and night returns are negative for all Vega-Theta portfolios.

All moneyness and maturity categories have positive day and negative night returns. Thus, the day-night return asymmetry will be observed for any combination of options with positive weights. For example, call and puts can be combined into a synthetic variance swap, a key portfolio for studying the variance risk premium. Thus, according to this argument, the day-night effect will be also observed for variance swaps.

Most of option return variation across maturity and moneyness is due to option leverage. In Table A.3, we report the deleveraged returns for S&P index options by moneyness and time-to-expiration. As expected, return signs are not affected but magnitudes decrease sharply after deleveraging. Average returns become comparable across time-to-expiration and are weakly decreasing in moneyness. Most t-statistics remain significant for both day and night deleveraged returns.

To explore how option returns depend on market conditions, we sort trading days into portfolios based on market volatility, tail risk, option liquidity, interest rates, and investor sentiment. Consistent with visual evidence in Figure 2, Panel A of Table 6 shows that market conditions produce little variation in overnight returns. Night returns are slightly more negative when VIX is high, and interest rates and investor sentiment are low. Intraday returns on the other hand are extremely positive when volatility is high (0.97% per day) or option liquidity is low (0.57% per day). Interestingly, intraday returns also depend differently on the two measures of investor sentiment that we use. The returns are increasing in the AAII investor sentiment, which is based on a survey of how bullish investors are about the stock market, but are decreasing in the Baker and Wurgler (2006) sentiment.[14] Interestingly, the BW sentiment is the only variable that produces significant high-low spread for both night and day returns (-0.62% and -0.54%). Next, we use two popular tail risk measures proposed by Kelly and Jiang (KJ, 2014), and Du and Kapadia (DK, 2012) to explore whether rare disasters or tail risk can explain the day-

[14] Baker and Wurgler sentiment consists of six components including closed-end-fund discounts, market turnover, equity issuance, number of IPOs, and their first day return. Baker and Wurgler (2006) provide sentiment index data only until 2010 at the time of our analysis.

night effect. Panel B of Table 6 shows that systematic tail risk produces little variation in either day or night option returns.

Finally, we show the day-night option returns asymmetry cannot be explained by S&P 500 index returns and VIX futures returns. Table A.6 estimates a regression of index option returns on VIX futures returns and index returns separately for day and night periods. First, delta-hedging works reasonably well as the coefficient for index returns is zero for intraday period and is relatively small for overnight. Second, intraday returns for options and VIX futures are highly correlated with t-statistics of 17. However, night returns are much less correlated as the coefficient is lower than for the intraday regression (0.66 vs. 0.92), and the t-statistics is "only" 5.6. Perhaps, the options and volatility futures markets are less integrated during overnight period. Importantly, volatility and market risk factors explain only a tiny portion of the day-night effect. Indeed, the intercept, which corresponds to alpha/abnormal returns, is 0.24% for the intraday case and is only slightly smaller than average intraday return of 0.28%. Overnight return decreases from -1.08% to -0.89% after controlling for market and volatility factors.

4.3. Intraday Patterns in Option Order Flow

In this section, we study how option investors trade intraday. To our knowledge, we are the first to study option order imbalances over intraday sub-periods. Following the literature, we compute order imbalance as the difference between the number of buyer- and seller-initiated trades divided by total number of trades; thus, it is between -100% (if all trades are sells) and 100% (if all trades are buys). It is widely believed that investors are generally buying put index options and writing covered calls (long stock, short OTM call) in equity options. We confirm this fact; however, the order flow is much more balanced than expected. Table 7 shows that average order imbalance for index puts (calls) is 3.2% (0.9%). That is, out of 1000 put trades only 516 are buyer-initiated and the remaining 484 are seller-initiated. Similarly, for equity options, call and put order imbalances are -5.5% and -1.7% respectively. Thus, call writing and protective put strategies do not seem to dominate option trading in the recent period.

How do imbalances evolve over a trading day? While equity option imbalances do not vary much across intraday sub-periods, index option imbalances do. In the morning, investors tend to buy index puts (a 2% imbalance) with zero imbalance in index calls, but in the afternoon, they start buying more calls and puts. Imbalance for call options becomes positive (2%), and put imbalance increases to 5%.

A 3% increase in put order imbalance from morning to the afternoon has several implications. First, this increase is consistent with positive intraday option returns; however, such small imbalance is unlikely to make enough price pressure to explain intraday returns. Furthermore, any anticipated order imbalances should be reflected in prices in advance. Second, this result rejects a popular hypothesis in the options literature that option investors trade aggressively around the close. We find that order flow is not that different around the close. Finally, increasingly positive imbalances are consistent with investors not being aware of the day-night option return effect. The day-night effect encourages volatility sellers (sell options and then delta-hedging them) to execute their trades in the afternoon rather than morning. Investors who sell options in the morning suffer from positive intraday returns and are not compensated for taking intraday volatility. Contrary to this prediction, option order imbalance is slightly more positive in the afternoon, i.e., investors buy more instead of selling. Thus, an average option investor does not take advantage of the day-night effect. This fact implies that option market-makers do not lose money by posting biased option prices.

Overall, we document several stylized facts about option order flow and relate them to potential explanations for the day-night effect, which we further discuss below.

5 Potential Explanations

So far, we have documented puzzling empirical facts about option returns, which is our main result. In this section, we try to explain them with a wide range of potential explanations including risk-based option pricing theories, financial frictions, and finally behavioral explanations. Although, most of these explanations are consistent with some of the facts, almost all of them struggle to replicate the day-night return asymmetry. However, we introduce a behavioral theory, the volatility seasonality bias that fits most empirical facts relatively well. This makes us focus on testing it. Overall, multiple explanations likely contribute to the day-night effect, but the volatility bias is by far the most promising.

5.1. Challenges for Rational Explanations

In this section, we explore potential rational explanations for the day-night return asymmetry. Positive intraday option returns are particularly hard to reconcile, even zero returns would be puzzling. Also, the proposed theories should not only explain the day-night return asymmetry but also its cross-asset variation. For most ETFs and individual stocks, option returns are positive intraday but for some the pattern is reversed with positive returns overnight.

In conventional models, negative average option returns compensate investors for taking volatility and jump risks. The intuition is simple. A long delta-hedged position in a call or a put has a (convex) V-shaped payoff: it makes money if the underlying price deviates significantly from its current level. Thus, this option portfolio provides valuable insurance against market crashes and should earn negative excess returns (negative risk premium). Investors must be compensated for taking this risk. Numerous theoretical papers formally show this point. For these models to explain the day-night return asymmetry, we have to assume that option investors are averse to overnight volatility/jumps, but love intraday volatility so much, that they are willing to take the intraday risk for free or even pay for it. For example, imagine that investors hate jumps and love stochastic volatility, and maybe most jumps occur overnight, hence negative overnight returns, and the only risk intraday is stochastic volatility, but investors love it, hence positive intraday returns. Yet extending this example to explain the cross-asset variation in the day-night effect is a bit more challenging. Overall, if these theories indeed are responsible for the day-night effect, this has striking implications about option investors' risk-aversion (i.e., risk loving). Several of our tests indirectly speak to this explanation. First, day and night option return distributions are similar (except of course for the mean), implying similar risk profiles for the two periods (Table 1). Second, overnight returns do not depend on the ex-ante jump measures (Panel B of Table 6). Third, the stochastic process for the underlying is not that different across the two sub-periods (Table 2) and if anything the overnight period has lower stock return variance. Fourth, if night returns are risky, then a strategy of selling volatility overnight should occasionally lose money, yet it is profitable in every three-month period (Figure 2).

Peso problem can potentially explain many of asset pricing anomalies. The idea is that a given sample may be unrepresentative because it missed a "rare disaster," which typically triggers large negative stock returns (e.g., a war). Peso problem can potentially explain why night returns are so negative; however, missing a rare disaster would worsen the intraday return puzzle. A disaster triggers extreme returns in the underlying, that translate into large positive returns for a delta-hedged option portfolio. Overall, peso problem implies that the "true" average return is even more positive than our estimate. Also, if peso problem is important, night and day returns should depend on the ex-ante disaster likelihood as captured by the tail risk measures, but they do not depend in the data (Panel B of Table 6). It's also not clear how peso problem can fit the cross-asset patterns. We also want to mention a "reverse" peso problem. Maybe our sample contains too many rare disasters. However, our main results hold even after excluding the financial crisis. Overall, peso problem is useful for explaining why option returns are so negative over longer horizons, but it struggles to explain the day-night asymmetry.

We next consider several financial frictions that are particularly large during overnight period. For one thing, option market-makers (OMMs) cannot adjust their option positions at night because the market is closed. Relatedly, this period is also special because the underlying market is liquid intraday but is illiquid overnight. Thus, while OMMs can delta-hedge frequently and seamlessly during the trading day, they cannot adjust their hedges during overnight.[15] Although return variance is larger intraday, volatility of an option portfolio can be substantially reduced intraday by frequent delta-hedging (index futures). As a result, the night period has more residual volatility and is riskier in this sense. Therefore, option investors may require a larger premium to carry positions overnight. This natural theory may explain why night returns are more negative than day returns. Unfortunately, it struggles to explain the remaining facts. First, it predicts that intraday returns should be also negative (just less negative than night returns). Second, night returns should be more negative when volatility is high (high VIX) as the overnight risk is proportional to OMM's risk-aversion, position size, and volatility. But night returns depend little on volatility (Table 6). Finally, as after-hours

[15] For example, Figlewski (1989) shows that even with frequent delta-hedging the residual standard deviation that remained unhedged is large. Thus, even small transaction costs make the market incomplete.

trading in index futures became more liquid in recent year, adjusting delta-hedges became easier overnight, and thus night returns should be less negative in recent years, but they didn't change (Table 4). Overall, OMMs certainly cannot properly hedge overnight and thus are exposed to significant overnight jump risk. This friction can potentially explain why night returns are so negative; however, it has less success explaining the day-night asymmetry.

Overnight period is also special because funding and margin costs are usually incurred overnight (and thus are small intraday). These large overnight costs imply that the day-night effect should be more pronounced when interest rates are high. However, night returns are slightly more negative when interest rates are low (Table 6). Also, such costs implied that intraday option returns should be similarly positive for all securities and thus cannot explain the cross-asset variation in the day-night effect.

Branger and Schlag (2008) formalize several concerns about option returns that are relevant for our results. First, they argue that option pricing models and thus option deltas are often misspecified. This is certainly true in practice, even practitioners cannot agree on whether deltas should be greater or smaller than deltas from the BSM model. Thus, "delta-hedged" option portfolios may have residual delta exposure. If this residual delta is positive, and the positive equity risk premium exceeds the negative variance premium, then intraday option returns can be positive on average. If most of the equity risk premium occurs overnight, this fact may also contribute to option returns asymmetry. Branger and Schlag also introduce the "discretization bias". Surprisingly, the average delta-hedged returns are slightly positive even in the BSM world with unbiased deltas. They show that the discretization error in option returns is high then the equity risk premium and option gamma are high, and the delta-hedging frequency is low. This explanation is one of the few that naturally produces positive option returns. We conduct several tests to explore the implications of these two hypotheses. First, both day and night option returns stay virtually unchanged after controlling for contemporaneous underlying returns (Table A.6). This regression is akin to accounting for "empirical" deltas and eliminates any obvious delta biases. Second, average intraday returns depend little on delta-hedging frequency (Figure A.2). More frequent delta-hedging decreases the discretization error. If this error is the primary driver of the positive intraday returns, then the returns should be sensitive to the hedging frequency, but they are not. Third, Branger and Schlag use pretty extreme parameter values such as the equity premium of 20%, volatility of 4%, and weekly delta-hedging. In untabulated results, we simulate the BSM model with parameters that match our historical data and found that the discretization error is small compared to intraday returns. Fourth, the discretization error would make both day and night returns more positive. Thus, this error alone cannot explain the return asymmetry, and something else (perhaps the inability to hedge overnight) makes overnight returns so negative. Finally, we further address concerns about delta-hedging by confirming our main result for straddle and raw option returns. Overall, the discretization error and biased deltas are probably responsible for some of the intraday returns, and despite the above tests we cannot fully eliminate the possibility that a non-linear interaction of these factors can lead to the observed return pattern.

A related concern is that the day-night effect is somehow mechanical because, following the literature, we compute option returns from the quote midpoints. To address it, we show that the size of the day-night effect does not depend on the option bid-ask spread (Table 6) and alternative return specifications such as computing returns from only bid or only ask prices (Table A.9). We also compute returns using trade prices instead of the quote midpoints (Table A.8). Finally, the correlation between day and night returns is close to zero unlike a pronounced negative correlation typical for a mechanical case (e.g., if open or close prices are "special" compared to other intraday prices).

If investors buy a lot of options, this price pressure can cause positive intraday returns by pushing option prices higher. And perhaps, night returns are so negative because part of the positive price pressure is reversed overnight. This price reversal implies a negative correlation between day and night returns, but the actual correlation is close to zero. However, one of our tests is consistent with the price pressure hypothesis. We find that investors on average buy index calls and puts, and even more so in the afternoon (Table 7). The order imbalance is relatively small though (3-5%) and is unlikely to significantly push prices. Also, order imbalance for equity options does not match positive intraday returns. Finally, option prices should reflect any anticipated order imbalances in advance. If OMMs expect positive order imbalances tomorrow, they will raise prices today. Overall, price pressure may contribute to positive intraday returns but its effect seems relatively small.

Although S&P 500 index options are some of the most important and actively traded options in the world, their trading costs are large. The effective bid-ask spread is more than 6% on average, and it decreased little over time.[16] Although we tentatively show in Section 5.6 that arbitrageurs with good execution algorithms can potentially make after-costs profits (they of course can also provide liquidity with limit orders), selling volatility overnight is not profitable after costs for most investors. Investors can still reduce their trading costs by executing option buys in the morning and sells in the afternoon. Overall, large transaction costs can explain why arbitrageurs do not eliminate the day-night effect, but not why this anomaly exists in the first place.

In summary, many of these theories have implications for negative overnight and long term option returns, but only few can produce positive intraday returns. The discretization bias and positive intraday imbalances potentially contribute to the intraday returns. Conventional jump and stochastic volatility theories are promising if we can understand why investors love taking intraday risk. Transaction costs explain why the effect is not arbitraged away.

5.2. Behavioral Explanations

Given that rational theories have limited success explaining positive intraday returns, we now turn to behavioral explanations. Even for them fitting the facts is not easy. For example, we first hypothesized that option investors may fail to continuously adjust time-to-expiration during the trading day and thus overstate option maturity by almost one day at the close. This hypothesis generates positive day and negative night returns but fails to match the cross-asset variation of the day-night effect. Luckily, these cross-sectional patterns hinted us at the volatility bias explanation. Option prices underreact to the day-night seasonality in the underlying volatility.

We propose the "volatility seasonality bias," option prices correctly reflect the total daily volatility in the underlying. However, they get wrong the split between intraday and overnight volatilities by ignoring the day-night volatility seasonality. The

[16] We compute effective spreads as twice the difference between trade price and the pre-trade quote midpoint, adjusted for trade sign and normalized by option price.

underlying volatility is much higher intraday than at night, which is perhaps the strongest known volatility seasonality. Thus, total volatility during the life of an option can be viewed as a sequence of high (intraday) and low (night) volatility periods stacked together. Option prices are proportional to the total return variance expected before expiration and thus should reflect this seasonality. Compared to the no-seasonality (equal volatility) case, option prices (and implied volatility) should be slightly higher at open, when high volatility periods outnumber lower volatility periods by one.

It is more intuitive however to think about this phenomena in terms of option returns rather than prices. Option returns are proportional to the difference between realized and implied return variances. Implied volatility is usually set above the expected realized volatility, which leads to the negative average option returns. The failure to account for the volatility seasonality translates into option returns. Positive intraday returns indicate that option prices systematically understate intraday volatility, and similarly large negative night returns suggest that overnight volatility is overstated. Option close prices are too high and open prices are too low. Figure A.1 in the appendix illustrates how the volatility seasonality bias affects the relationship between implied and realized volatilities.

Overall, the volatility bias fits the basic facts. Day returns are positive and night returns are too negative because perhaps option prices underreact to the day-night volatility seasonality. In the next sections, we further show that an option pricing model with day-night volatility seasonality and underreaction produces plausible day-night option return magnitudes. We also test that the cross-asset variation in the return asymmetry is mostly due to the variation in the day-night volatility seasonality. These two tests convinced us that the volatility bias is a major contributor to the day-night return asymmetry.

We also consider another plausible behavioral explanation – perhaps option market-makers only adjust time-to-maturity at open instead of continuously changing it during a day. That is, a 30-day option is assumed to remain exactly 30-day during the entire trading day, and becomes 29-day only at the next-day open. As option prices are increasing in time-to-expiration, this bias causes closing prices to be too high and thus makes option returns negative at night and positive intraday. Although this theory produces the option return asymmetry, it fails on other dimensions. In untabulated results, we simulate a Heston economy with this time-to-maturity bias. In the simulations, if we match the overnight return magnitude with the data, intraday returns are too large. Furthermore, the time-to-maturity bias implies that overnight option returns should always be equally negative for all ETFs/stocks, which is not true in the data. Overall, even finding a behavioral theory for the day-night effect is difficult, which makes it even more remarkable how the volatility seasonality bias matches the stylized facts so well.

5.3. Day and Night Volatility

Before testing the volatility bias explanation, we want to explore its main ingredient, the day-night volatility seasonality. We explore the seasonality for individual stocks and S&P 500 index. Although it is well-known that volatility is higher intraday, surprisingly little is known about how much higher it is. Using five stocks between 1974 and 1977, Oldfield and Rogalski (1980) find the day-night volatility ratio of 2.06. For 50 stocks from Tokyo exchange, Amihud and Mendelson (1991) show that volatility is higher in trading compared to non-trading periods. Converting their estimates of overnight and daily return variances produces a day-night volatility ratio of 1.49. Stoll and Whaley (1990) find the volatility ratio of 2.3 for NYSE stocks during 1982 through 1986. Surprisingly, more recent references are hard to find. These estimates are broadly consistent with what we find in our sample.

To compute the day-night volatility ratio, we first compute night (close-to-open) and day (open-to-close) volatilities as standard volatility but with close-to-open and open-to-close returns. I.e., night volatility is an average of a square root of the sum of squared close-to-open returns over the previous 60 days. We do not annualize volatility and do not adjust for the day and night length differences. To make day and night volatilities comparable on the per-hour basis, intraday volatility can simply be multiplied by 1.64 ($= \sqrt{17.5/6.5}$) as night and day periods are 17.5 and 6.5 hours respectively. We then compute a simple ratio of the intraday and overnight volatilities.

Figure 3 shows the two volatilities and their ratio for S&P500 index over our sample period. Both volatilities expectedly spike during the financial crisis and remain low otherwise. However, the volatility ratio is surprisingly stable even during the crisis.

The ratio slowly decreases from about two in 2004 to about one in 2013. The ratio of 1 still means that *per-hour* volatility during the day is 1.6 times of overnight volatility. Most of the decease occurred during the late 2007 to 2009 period, then the stock liquidity improved substantially due to regulatory changes. Interestingly, the decreasing trend in total volatility that received so much public attention recently (as volatility is close to historical low now) is due to the decline in intraday rather than overnight volatility. We also explore the volatility ratio trends for individual stocks. Figure A.3 in the Appendix shows how distribution of the volatility ratio across stocks (quantiles and the mean) evolved over the sample period. Average volatility ratio declined from 2 to 1.7, which is much less than for the index. The distribution is quite symmetric with mean and median tracking each other closely. Top and bottom 10% percentiles have a volatility ratio of 2.7 and 1.0 respectively and are persistent over time.

The fact that the day-night volatility ratio does change over time is important. The volatility literature typically estimates realized volatility from intraday data and then annualizes it using an ad hoc day-night volatility ratio. We argue that the day-night volatility ratio should be estimated carefully, otherwise such volatility estimates may be substantially biased.

Overall, the volatility ratio fluctuates in a relatively narrow range (e.g., from 1 to 2 for the index), we use this range later to simulate day and night option returns for a grid of plausible volatility ratio values. We leave for future research to understand the trends in the volatility ratio.

5.4. Cross-Sectional Tests of the Volatility Seasonality Bias

The volatility seasonality bias can certainly match the sign of day-night option returns. We conduct two major empirical tests to further validate it. The next section shows that the bias can produce the return magnitudes observed in the data by simulating option returns in a model with the volatility bias. In this section, we explore cross-stock implications of the bias. Our main test is inspired by the anecdotal evidence from select ETFs in Section 4.1. The volatility bias implies that stocks with more pronounced day-night volatility seasonality should have higher day-night asymmetry in option returns. Indeed according to the bias, option prices ignore that day and night volatilities are above and below the overall average volatility (day + night). Thus, the more intraday volatility deviates from the overall average, the more positive intraday option returns are, hence higher return asymmetry. The day-night volatility seasonality measures this volatility deviation and is computed as a simple ratio of intraday and night volatilities, $\lambda_t^i = \sigma_{day,t}^i / \sigma_{night,t}^i$, where intraday volatility, $\sigma_{day,t}^i$ ($\sigma_{night,t}^i$), is computed as standard deviation of intraday (night) underlying returns. This volatility ratio is around 1.8 for an average stock.

We can apply this test to the S&P 500 index time-series or to the cross-section of optionable stocks. For S&P 500 index, it is hard to reliably estimate time-variation in average returns and volatility, and we lack statistical power. Therefore, stock cross-section is a more natural testing ground with more than a thousand stocks on a typical day, and the volatility ratio ranging from one to three. Similar to the cross-section of stock return tests, we can implement this test with portfolio sorts or Fama-MacBeth regressions. The portfolio test sorts stocks into five portfolios based on their historical day-night volatility ratio, and then day and night option returns are computed as an average over all stocks in a given portfolio. As Table 9 shows, the day night volatility seasonality varies from one to three between bottom and top portfolios. The ratio of one still means that per-hour volatility during the day is 1.6 higher than during the night. As predicted by the volatility bias hypothesis, as the day-night volatility ratio increases, night returns decrease from -0.33% to -0.52%, and intraday returns increase from -0.03% to 0.26%. The corresponding t-statistics for the difference between high and low portfolios are -11 and 18. These portfolio sorts confirm that the day-night volatility seasonality is a major driver of the day-night option return asymmetry.

We prefer Fama-MacBeth regressions to portfolio sorts though, because they let us control for other factors affecting option returns. We estimate separate regressions for day and night returns as dependent variables and report the results in Table 8. The setup and interpretation are very similar to the cross-section of stock returns tests. If no controls are included, then the intercept equals to the mean of the dependent variable, which are the average day and night option returns in our case (0.1% and -0.4%). Next, we want to explain the negative night and positive day intercepts by adding explanatory variables to these two regressions. The day-night volatility ratio is our main explanatory variable. As we add it to the intercept-only regressions, two notable changes occur: (i) the volatility ratio is indeed highly significant and (ii) the intercepts in day and night regressions become similarly negative. First, the coefficient for the volatility ratio is positive (0.17) in the intraday regression. That is, higher day-night volatility ratio corresponds to more positive intraday option returns, exactly as predicted by the volatility bias hypothesis. Similarly, the ratio has a negative coefficient (-0.14) in the overnight regression. That is, night returns are more negative if the volatility ratio is high. Both results are highly statistically significant (t-statistics of 14 and -12) even after accounting for autocorrelation in the volatility ratio. Overall, this result directly supports the volatility bias explanation. Interestingly, the coefficients match in magnitude but differ in sign ($0.17 \cong |-0.14|$). The next section explains that it's not a coincidence: this pattern is implied by the volatility bias if option prices completely ignore the day-night volatility seasonality. Second, the intercepts change from (0.1%, -0.4%) to (-0.15%, -0.26%) after controlling for the volatility ratio. This means that after accounting for the day-night volatility seasonality, the abnormal option returns in the day and night sub-periods are similarly negative ($-0.17\% \cong -0.26\%$). Perhaps, OMMs do not charge additional return premium for the overnight period after controlling for the volatility bias, but a more detailed analysis is needed here. Finally, all these results generally hold after including control variables as shown in the last two columns of Table 8.

Importantly, if there is an issue with the measurement of volatility, e.g., maybe the right measure is the per-hour volatility ratio or the variance ratio, this is not likely to affect this cross-asset analysis because the volatility ratio for every stocks is likely multiplied by the same number. The portfolio sort analysis is immune to any monotonic transformation of the volatility ratio.

Overall, this cross-sectional test strongly supports the volatility seasonality bias explanation of the day-night effect. Specifically, the day-night volatility ratio negatively (positively) predicts subsequent night (intraday) option returns across stocks, exactly as implied by the volatility bias. The next section introduces a simple model that helps us interpret some of the coefficient relationships found above.

5.5. Option Pricing Models with Volatility Seasonality

In this section, we add the day-night volatility seasonality to the Black-Scholes-Merton (BSM) and Heston models. In the model, we control for how much option prices underreact to the volatility seasonality and thus can study the volatility bias in controlled settings. Assuming realistic parameters, these models produce not only the signs but also the magnitudes of the day-night option returns. This calibration exercise also implies that option prices not simply underreact but completely ignore the day-night volatility seasonality. Furthermore, we confirm the cross-stock results from the previous section as we find similar regression results in a simulated panel of option returns from the BSM model. It is also reassuring that both models produce similar results.

Let us briefly summarize the setup. We put implementation details in Sections A.3 and A.4 in the Appendix because the volatility seasonality can be easily added to standard option models. Our methodological contribution is modest, simulation results are the interesting part. First, we take standard BSM and Heston models and adjust the volatility process for the underlying to add the day-night seasonality. For the BSM model, this simply means that day and night volatilities are set to constants such that $\sigma_{day} > \sigma_{night}$. For the Heston model, instantaneous spot variance is multiplied by a constant scaling factor, such that $\nu^{day} > \nu^{night}$. Microstructure literature indeed shows that volatility jumps around open and close validating this assumption. Obviously, these models operate with instantaneous (per second) volatilities, but these parameters can be easily set to match the target day-night volatility ratios, which we do not adjust for the difference in day-night length to compare them with results from the previous sections. We set implied volatility in the BSM model higher than realized volatility to generate the variance risk-premium. Second, we solve for option prices using a simple closed-form formula for the BSM model and Monte-Carlo simulations for the Heston model. So far, we assumed that OMMs, who price options, know the true day-night volatility ratio. What if they don't? What if they underreact to the volatility seasonality or even completely ignore it? We model this so that option prices reflect total volatility correctly but use the "wrong" day-to-night volatility ratio. We simulate the underlying with true volatility ratio, $\lambda\ (= \sigma_{day}\ /\ \sigma_{night})$, but compute option prices using OMM's beliefs about volatility ratio, λ^{IV}. In two special cases, OMMs can have rational beliefs if

$\lambda^{IV} = \lambda$, or they can completely ignore the day-night volatility and assume the same per-hour volatility during day and night if $\lambda^{IV} = 0.61 = \sqrt{6.5/17.5}$, where trading day is 6.5 hours. We then compute option returns similarly to actual option data as described in Section 3. That is, we keep the same return methodology but now control the price generating process.

We set model parameters to match historical data and Broadie et al. (2007). We summarize them in Table 10. Keeping other parameters fixed, we simulate the model for different degrees of the day-night volatility ratio λ and underreaction to the volatility seasonality λ^{IV}. λ is set to (1, 1.5, 2, or 2.5) to match the plausible range of day-night ratios for S&P500 index in Figure 3. OMM's beliefs about the volatility ratio λ^{IV} take the same values (1, 1.5, 2, or 2.5) and also $\lambda^{IV} = 0.61$, which is the "totally ignore the seasonality" case. Importantly, these parameters affect the split between intraday and night volatilities but not the daily total. Thus, the choice of (λ^{IV}, λ) affects average day and night option returns individually but not their sum, which is -0.7% per day and matches the numbers in Figure 1.

Two main results emerge in the simulations. Frist, the models are able to replicate day-night return magnitudes in the data if option prices completely ignore the day-night volatility seasonality. Second, day-night option returns depend primarily on OMM's perceived volatility ratio λ^{IV}, and much less on the actual volatility ratio λ.

Figure 4 shows how average day and night option returns for the BSM model depend on (λ^{IV}, λ). Consider $\lambda = \sigma_d/\sigma_n = 1.5$, the average day-night volatility ratio in the data. If OMMs have rational believes $\lambda^{IV} = \lambda$, then both day and night option returns are negative (-0.50% and -0.22%). As the perceived volatility ratio λ^{IV} decreases, and thus the volatility underreaction increases, the asymmetry between day-night option returns increases too. That is, night returns become more negative, and intraday returns - less negative. In the extreme "full bias" case, then OMMs completely ignore the day-night volatility seasonality ($\lambda^{IV} = 0.6$), intraday returns become positive 0.10%, and overnight returns are -0.84%. These simulated returns are remarkably close to the option returns observed in the data (-1.04% and 0.28% in Table 1)! The return pattern is similar for other plausible volatility ratios λ. Returns are generally negative, but for the "full bias" case intraday returns become slightly positive (ranging from -0.04% for $\lambda = 1$ to

0.23% for $\lambda = 2.5$). Overnight returns vary from -0.70% for $\lambda = 1$ to -0.96% for $\lambda = 2.5$. Thus, the return results are not particularly sensitive to the true volatility ratio λ, and are depend mostly on λ^{IV} that OMMs use to price options.

Figure 5 shows results for the Heston model, which is a more realistic way to introduce the negative variance risk premium. The results are similar to the BSM model except that intraday returns are less negative on average. For example, if the volatility ratio is $\lambda = 1.5$, and option prices ignore the volatility seasonality, then night and day returns are -1.05% and 0.45%, again remarkably close to the historical returns. Returns depend to the volatility ratio λ but are not too sensitive. As the ratio increases from one to two, day and night returns change from 0.16% to 0.57% and from -0.79% to -1.21%, for the full bias case. That is, intraday returns are slightly positive for all λ.

This model also predicts that, if option prices underreact to the volatility seasonality, the correlation between day and night option returns must be close to zero, which we confirm in simulations. This correlation is indeed close zero in the data (0.02), which validates our hypotheses.

The BSM model can be also used to simulate the cross-sectional implications of the volatility bias (Heston model is too computationally expensive here). These simulations help interpret our cross-stock results in Table 8; in particular, (i) stocks with higher day-night volatility seasonality have more pronounced day-night option return asymmetry and (ii) the remarkable coefficient patterns for the volatility ratio. Indeed, we show that these patterns are implied by the model with the volatility bias. We simulate a panel of option returns for a cross-section of a hundred stocks, each with its own volatility ratio, λ. We assume the full volatility bias case and uniformly draw λ from between one and three, which matches the range in actual data (see Table 9 and Figure A.3). In Table 11, we report results for the Fama-MacBeth cross-sectional regressions for simulated data. We find exactly the same patterns as in the regressions for actual data in Table 8. First, the intercept in the intraday return regression flips sign from positive (unconditional return) to negative after controlling for the volatility ratio. The negative conditional intercept reflects the true option risk premium embodied in the model, which is negative. T-statistics are large as we can simulate as much data as we want. Second, the volatility ratio positively (negatively) predicts intraday (overnight) returns. That is, the day-night return asymmetry increases with the volatility ratio. The coefficients for the volatility ratio λ in the day and night regressions have the same magnitude but opposite sign, $\beta_{day}^{\lambda} = 0.13$ and $\beta_{night}^{\lambda} = -0.13$. These coefficients are remarkably close to the coefficients in the regression for historical data ($\beta_{d}^{\lambda} = 0.17$ and $\beta_{n}^{\lambda} = -0.14$). Finally, also matching the data, both day and night option returns become negative after controlling for the volatility ratio.

Obviously, the BSM and Heston models are too simplistic to capture all the complexities of option prices and returns. However, it is reassuring that even these stylized models can replicate reasonably well the magnitudes of day and night option returns in the data with just the undereaction to the day-night volatility seasonality added to standard models. These results further support the volatility bias as the most promising explanation for the day-night return asymmetry.

5.6. Trading Strategy

Practitioners may wonder whether the day-night bias can be turned into a trading strategy by profiting from large overnight returns. The short answer is yes, but only for certain options and only for investors who are very careful about their trade execution (e.g., hedge funds specializing in both trading options and trade execution). The costs for an average investor are too high; however, he can still benefit from the day-night effect (i.e., reduce costs and risks) by executing their option sales in the afternoon instead of the morning. Importantly, marginal investors, who have low execution costs, not average investors, are responsible for arbitraging away such "good deals."

At first glance, the option trading costs are ridiculously large.[17] For example, the effective bid-ask spread for S&P 500 index options is about 6% in our sample. Hardly any option trading strategy is profitable after accounting for these spreads. Do most investors pay such large spreads? No, Muravyev and Pearson (2016, MP henceforth) show that most investors time their trades and pay lower spreads. Trade timers pay as

[17] We focus on the bid-ask spread as it is typically much larger than other option costs such as hedging costs in the underlying (e.g., Figlewski, 1989), brokerage/exchange commissions, margin/funding costs, execution uncertainty, and price impact; however, obviously, these costs should be accounted for in a more thorough analysis.

much as one fourth of the effective bid-ask spread when taking liquidity. Of course, investors can also reduce costs by providing liquidity with limit orders.

For the trading strategy, we focus on options on SPDR S&P 500 ETF (ticker SPY), the world's most liquid ETF, that are a close substitute for S&P index options but incur much lower transaction costs. Next, we compute trading cost measures introduced by MP (2016). That is, using the option trade data, we compute the effective bid-ask spread adjusted for the fact that many investors time their trades to reduce transaction costs. Following MP (2015), each trade is assigned the likelihood of being initiated by an execution timing algorithm, which let us to compute trading costs for two investor types: execution algorithms ("algos," who care about trading costs and time their trades) and everybody else ("non-algos," an average investor).

In Table 12, we compare overnight returns and trading costs for SPY options. Results are reported for two sub-periods – before and after the Penny Pilot reform that reduced the tick size for SPY options to one penny on September 28, 2007 (SPY options were launched in January 2005). An average overnight return for SPY options is -0.64% (an intraday return is 0.18%), and is identical before and after the Penny Pilot. However, trading costs decreased a lot after the tick size reduction. The costs for non-algos, which equal to the conventional effective bid-ask spread, decreased from 3.9% to 1.2%. Algo-traders' costs decreased from 0.66% to 0.05%. Thus, a hypothetical trading strategy that sells SPY options overnight and incurs transaction costs typical for an algo-trader breaks even in the pre-Pilot period (-0.01% = 0.65% - 0.66%), and is highly profitable in the post-Pilot period (0.6% per day) as the profits do not change while the costs decrease substantially. We use the transaction costs for algo-traders because they are the marginal investors in this high-cost market. Other investors' costs are too high to profit from this strategy. Overall, option trading costs decreased after the Penny Pilot making the overnight strategy potentially profitable for algo-traders, but only for them. Of course, the debate about the after-cost profitability of the overnight strategy does not answer a more fundamental question about why this effect exists in the first place.

6 Conclusion

In this paper, we document a striking pattern in average option returns. The returns are negative overnight but positive intraday. This result is robust to methodology choices and observed in different subsamples. We consider a number of potential explanations that help us understand option returns in general, but most of them struggle to explain positive intraday returns and the variation of the day-night option returns across stocks. The discretization bias and positive intraday imbalances potentially contribute to the intraday returns. Conventional jump and stochastic volatility theories are promising assuming investors love taking intraday risk. Obviously, transaction costs is a big factor for why the effect is not arbitraged away, they can't explain though why the anomaly exists in the first place. The day-night volatility bias is the most promising explanation. Perhaps, option returns become positive intraday because option traders completely ignore the well-known fact that stock volatility is much higher intraday than overnight. We conduct several tests that support this hypothesis.

These results improve our understanding of price formation in the options market but pose new challenges for future research. If option prices are indeed biased as the volatility bias implies, what does it mean? It‘s hard to imagine that OMMs (Citadel, Goldman Sachs), who are some of the most sophisticated investors, do not know about the day-night volatility seasonality. Volatility is obviously a major input to option pricing models, and these models can be easily adjusted to account for the volatility seasonality. Possibly, OMMs don't have incentives to adjust their models until they start losing money due to the day-night effect, but other investors trade as if unaware of the day-night returns. This argument emphasizes the important role that arbitrageurs play in forcing improvements in pricing models. Another possibility is that OMMs use a relatively simple model for volatility forecasting that probably includes first-order effects (volatility clustering, mean-reversion, leverage effect, earnings announcements) but ignores less obvious stylized facts such as volatility seasonalities. We leave for future research to explore whether other volatility seasonalities are properly reflected in option prices.

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Figure 1 Day and night average option returns

Overnight (close-to-open) and intraday (open-to-close) average delta-hedged returns for S&P 500 index options (Panel A) and equity options (Panel B). Returns are in percentage points per day; e.g., a -1.04% daily return for overnight index options. We also report 95% confidence intervals. Tables 1 and 2 complement this figure.

Panel A S&P 500 Index Option Returns

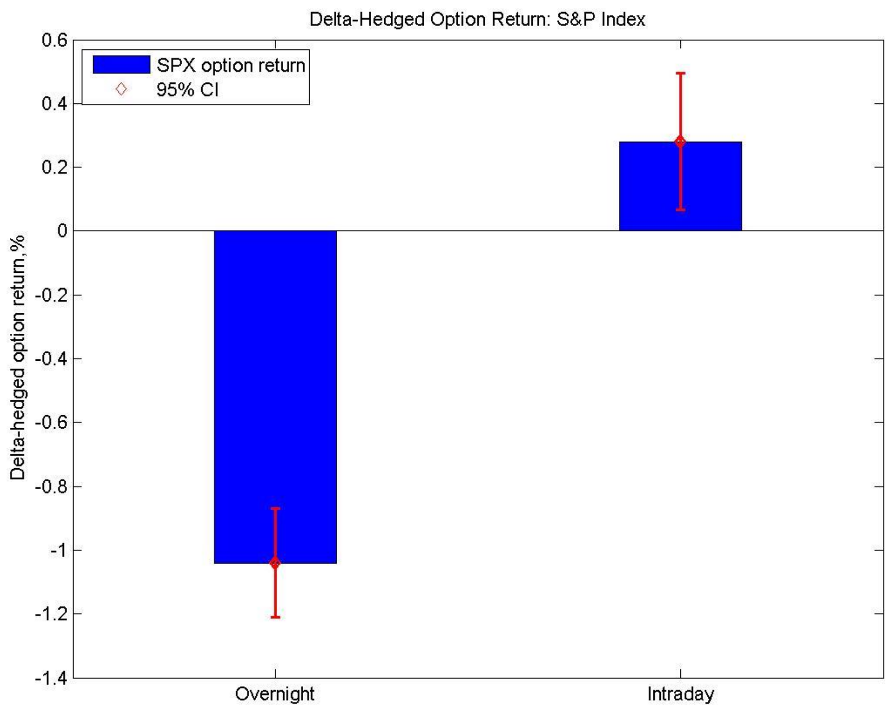

Figure 1 Panel B: Equity Option Returns

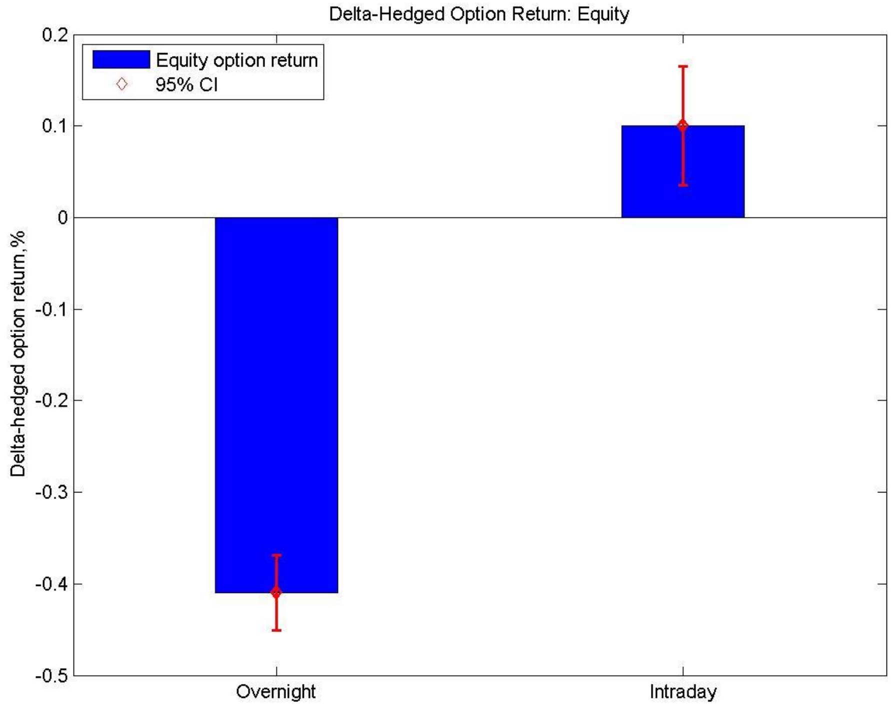

Figure 2 Profitability of two strategies that sell option volatility

Three-month rolling cumulative returns for two trading strategies that sell S&P500 index volatility (i.e., sell delta-hedged options). The conventional strategy keeps the position for the entire day (thin-dashed-grey line) while the proposed strategy that sells volatility only during overnight period (thick-solid-orange line). An investor sells calls and puts that traded at least once on a given day and then delta-hedges the position in the index futures market. Typical returns of these strategies are 30% per three months before transaction costs. Option returns are computed using quote midpoints.

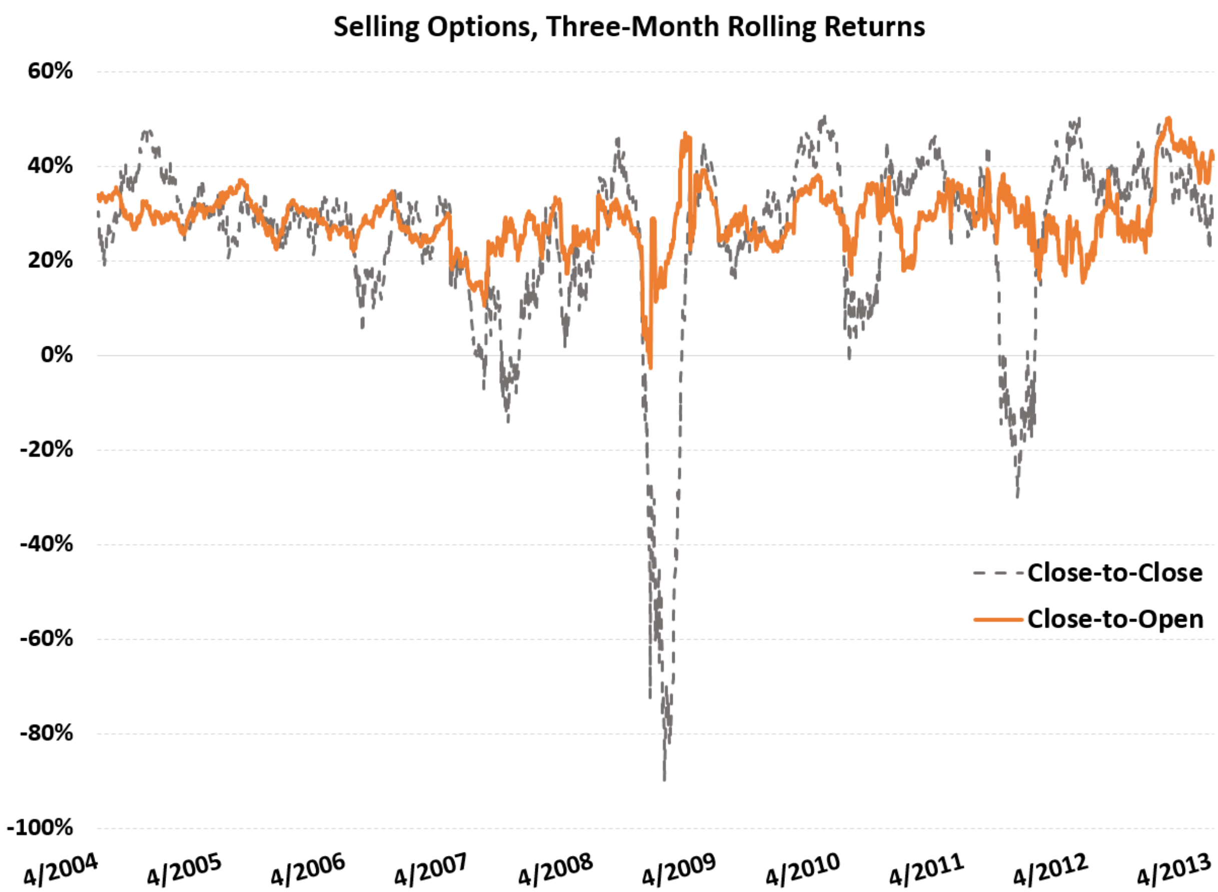

Figure 3 Day and night volatility for S&P 500 index

The top panel shows overnight (close-to-open) and intraday (open-to-close) volatility over the sample period. Overnight volatility is computed as an average of a square root of the sum of squared close-to-open returns over the previous 60 days. The bottom panel plots the ratio of the two volatilities. Note that the volatility is not annualized. Also, the ratio is not adjusted for the difference in length between intraday and overnight periods (to adjust multiple by 1.64). Figure A.3 in the appendix documents similar results for individual stocks.

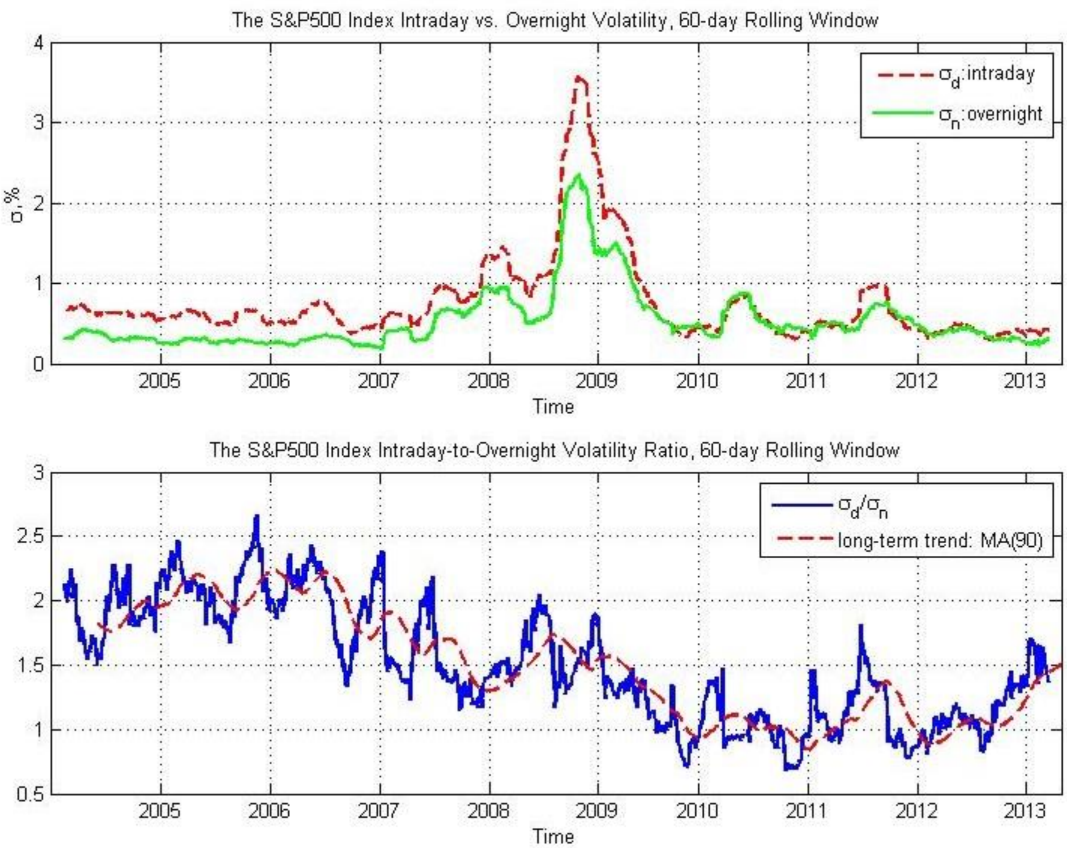

Figure 4 Day and night option returns in the Black-Scholes-Merton model

We study how day and night option returns depend on the day-night volatility bias in the BSM model. Model parameters are set to match the historical data. We simulate the model separately for different levels of the day-night volatility ratio ($\sigma_{day}/\sigma_{night} = 1, 1.5, 2, 2.5$), which cover range of plausible values in the data, and then compute average option returns. Each graph shows how night and day returns depend on the degree to which option prices underreact to the day-night volatility seasonality. While the actual seasonality is $\lambda \ = \sigma_{day}/\sigma_{night}$, option prices are set assuming a different ratio $\lambda^{IV} = \sigma_{day}^{IV}/\sigma_{night}^{IV}$, i.e., option investors have biased believes. In particular, *Full Bias* case means the option market maker completely ignores the volatility seasonality and treats: $\sigma_{day}^{IV} = \sigma_{night}^{IV} = \sigma^{IV}$. "No Bias" indicates cases then option prices are set using correct volatility ratio (i.e., unbiased beliefs). Also, the volatility ratio is not adjusted for the difference in length between intraday and overnight periods (to adjust multiple by 1.64).

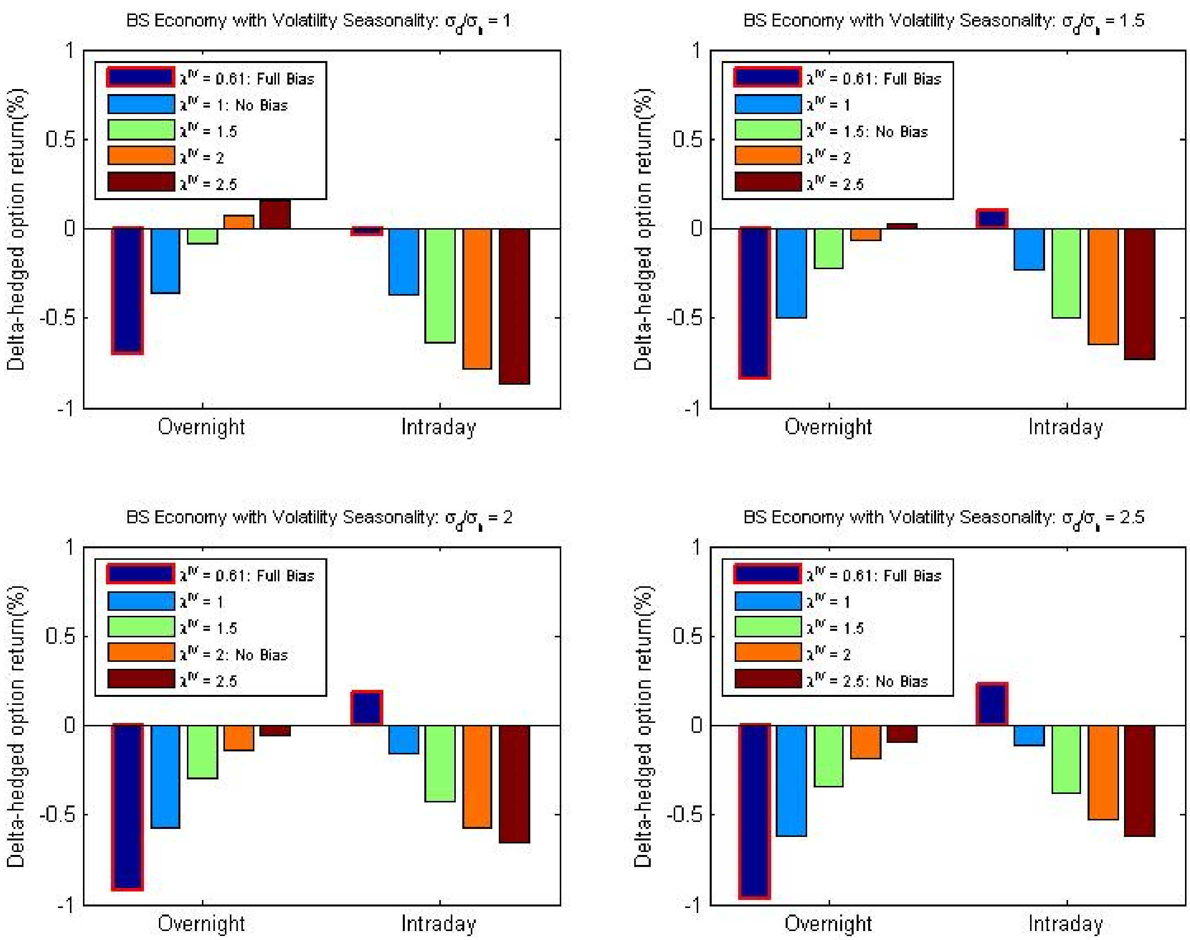

Figure 5 Day and night option returns in the Heston model

Similar to Figure 4, we study how day and night option returns depend on the day-night volatility bias in the Heston model. Model parameters are set to match the historical data. We simulate the model separately for different levels of the day-night volatility ratio ($\sigma_{day}/\sigma_{night} = 1, 1.5, 2$), which cover range of plausible values in the data, and then compute average option returns. Each graph shows how day and night returns depend on the degree to which option prices underreact to the day-night volatility seasonality. While the actual seasonality is $\lambda = \sigma_{day}/\sigma_{night}$, option prices are set assuming a different ratio $\lambda^{IV} = \sigma_{day}^{IV}/\sigma_{night}^{IV}$, i.e., option investors have biased believes. In particular, *Full Bias* case means the option market maker completely ignores the volatility seasonality and treats: $\sigma_{day}^{IV} = \sigma_{night}^{IV} = \sigma^{IV}$. “No Bias” indicates cases then option prices are set using correct volatility ratio (i.e., unbiased beliefs). Also, volatility the ratio is not adjusted for the difference in length between intraday and overnight periods (to adjust multiple by 1.64).

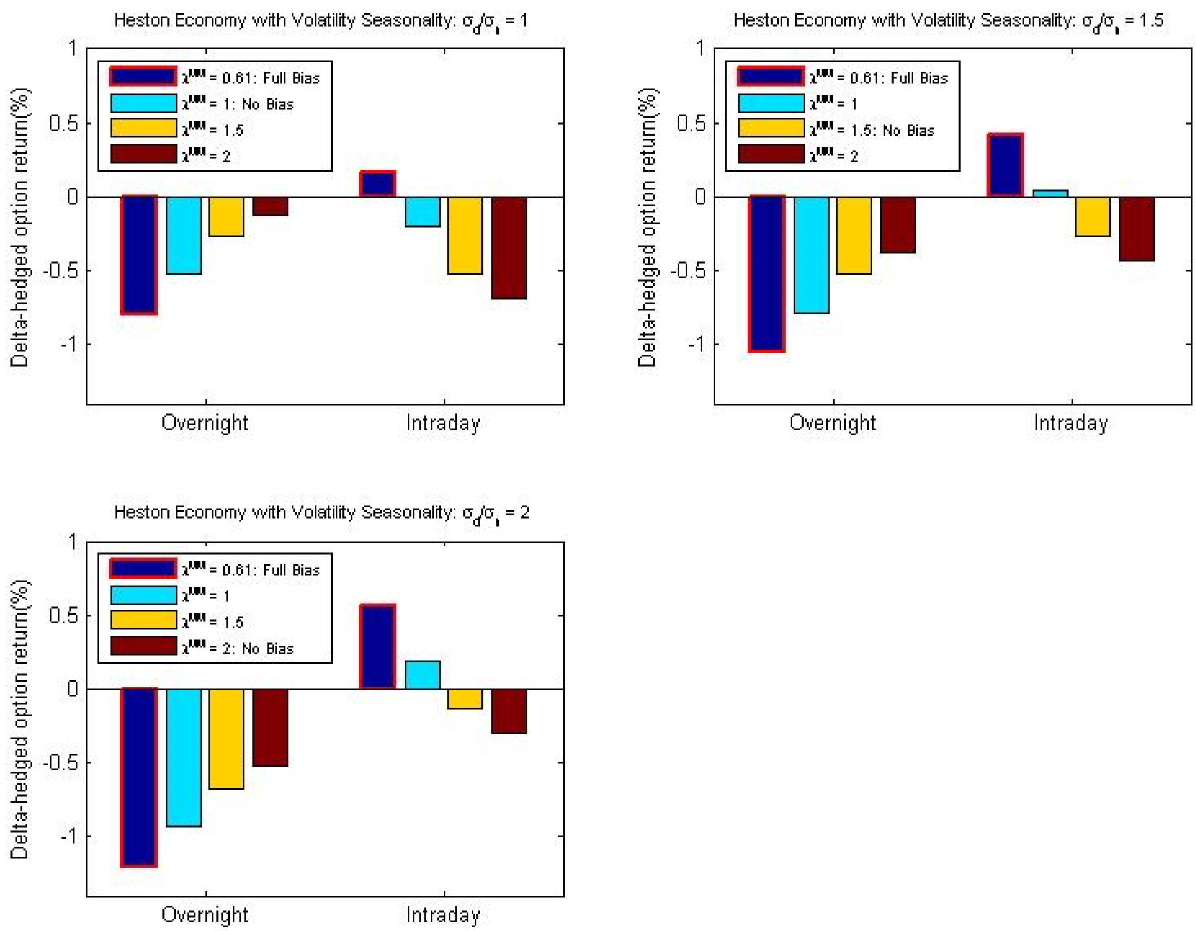

Table 1 Panel A   Day and night delta-hedged returns for S&P 500 index options

We report statistics for average daily returns, including their mean, standard deviation and 1%, 50%, and 99% percentiles. On each day, we compute average return for all options in a given category (e.g. OTM calls) and then report average across days. Returns are in percentage points per day; e.g., a 0.28% daily return for index options intraday. "All Deltas" include options with absolute delta between 0.1 and 0.9. Options are delta-hedged at the beginning of each sub-period.

		Intraday Returns, %					**Overnight Returns, %**				
	Moneyness	Mean	Stand. Dev.	1%	50%	99%	Mean	Stand. Dev.	1%	50%	99%
All	All Deltas	0.28	4.8	-8.70	-0.38	16.19	-1.04	4.5	-9.70	-1.24	11.25
	0.1 < |Δ| < 0.25	0.27	8.0	-14.63	-0.78	28.81	-1.74	6.2	-14.65	-2.03	18.20
	0.25 < |Δ| < 0.5	0.31	4.3	-7.94	-0.26	14.05	-0.89	3.3	-8.05	-1.15	10.61
	0.5 < |Δ| < 0.75	0.15	2.0	-3.84	-0.07	6.76	-0.53	1.8	-4.13	-0.69	5.35
	0.75 < |Δ| < 0.9	0.07	0.9	-1.68	-0.03	3.20	-0.22	1.0	-2.38	-0.32	2.88
Puts	All Deltas	0.24	4.6	-8.19	-0.35	15.97	-0.90	4.1	-8.83	-1.09	12.22
	0.1 < |Δ| < 0.25	0.20	6.9	-12.01	-0.70	24.72	-1.34	5.7	-11.28	-1.72	16.12
	0.25 < |Δ| < 0.5	0.23	3.7	-6.80	-0.25	11.98	-0.83	3.1	-7.91	-0.88	8.89
	0.5 < |Δ| < 0.75	0.18	2.2	-4.33	-0.07	7.28	-0.61	2.4	-7.05	-0.63	6.73
	0.75 < |Δ| < 0.9	0.14	1.3	-2.69	-0.01	4.20	-0.22	1.8	-4.88	-0.21	5.67
Calls	All Deltas	0.28	5.3	-9.97	-0.29	17.52	-1.17	5.0	-11.05	-1.43	12.02
	0.1 < |Δ| < 0.25	0.46	10.9	-20.75	-0.72	36.30	-2.23	8.5	-20.92	-2.85	25.56
	0.25 < |Δ| < 0.5	0.39	5.1	-8.85	-0.23	17.47	-1.05	4.1	-9.73	-1.47	12.27
	0.5 < |Δ| < 0.75	0.14	2.0	-3.73	-0.05	6.52	-0.50	2.1	-4.78	-0.71	6.14
	0.75 < |Δ| < 0.9	0.08	1.0	-1.91	-0.02	3.29	-0.21	1.3	-3.39	-0.35	4.02

Table 1 Panel B Day and night equity option returns

We report statistics for average daily returns, including their mean, standard deviation and 1%, 50%, and 99% percentiles. On each day, we compute average return for all options in a given category (e.g. OTM calls), then aggregate them across stocks. Summary statistics are reported for this aggregate equally weighted return (one number per day). Returns are in percentage points per day; e.g., a 0.10% daily return for equity options intraday. "All Deltas" include options with absolute delta between 0.1 and 0.9. Options are delta-hedged at the beginning of each sub-period.

		Intraday Returns, %					Overnight Returns, %				
	Moneyness	Mean	Stand. Dev.	1%	50%	99%	Mean	Stand. Dev.	1%	50%	99%
All	All Deltas	0.10	1.3	-2.69	-0.05	4.66	-0.41	1.1	-2.89	-0.43	3.41
	$0.1 < \lvert\Delta\rvert < 0.25$	0.05	2.5	-4.97	-0.18	8.84	-0.58	1.8	-4.96	-0.65	5.52
	$0.25 < \lvert\Delta\rvert < 0.5$	0.17	1.8	-3.65	-0.02	6.45	-0.49	1.3	-3.58	-0.52	4.27
	$0.5 < \lvert\Delta\rvert < 0.75$	0.16	1.0	-1.91	0.04	3.84	-0.31	0.8	-2.11	-0.33	2.80
	$0.75 < \lvert\Delta\rvert < 0.9$	0.16	0.6	-0.84	0.07	2.04	-0.10	0.4	-0.92	-0.13	1.50
Puts	All Deltas	0.21	1.3	-2.40	0.09	4.81	-0.49	1.2	-3.14	-0.50	3.54
	$0.1 < \lvert\Delta\rvert < 0.25$	0.23	2.3	-4.04	0.02	9.05	-0.54	1.7	-4.24	-0.59	4.72
	$0.25 < \lvert\Delta\rvert < 0.5$	0.29	1.5	-2.79	0.12	6.19	-0.50	1.2	-3.34	-0.51	4.02
	$0.5 < \lvert\Delta\rvert < 0.75$	0.27	1.0	-1.76	0.17	3.54	-0.33	0.9	-2.31	-0.39	3.25
	$0.75 < \lvert\Delta\rvert < 0.9$	0.26	0.6	-0.92	0.19	2.20	-0.12	0.6	-1.38	-0.16	1.93
Calls	All Deltas	0.07	1.8	-4.11	-0.08	6.37	-0.40	1.3	-3.80	-0.38	3.92
	$0.1 < \lvert\Delta\rvert < 0.25$	0.28	4.5	-9.89	-0.11	15.60	-0.53	2.8	-7.41	-0.69	9.35
	$0.25 < \lvert\Delta\rvert < 0.5$	0.25	2.6	-5.39	0.02	8.93	-0.47	1.6	-4.68	-0.48	5.42
	$0.5 < \lvert\Delta\rvert < 0.75$	0.09	1.3	-2.70	-0.03	4.64	-0.29	0.9	-2.48	-0.29	2.86
	$0.75 < \lvert\Delta\rvert < 0.9$	0.07	0.7	-1.34	0.02	2.42	-0.11	0.5	-1.13	-0.13	1.41

Table 2 Summary statistics for day and night returns for S&P500 index and individual stocks

This table reports the returns properties of the underlying (S&P 500 index and individual stocks). Panel A uses implied S&P500 index level from option prices while Panel B uses S&P 500 index futures. Returns and variances are not annualized and not adjusted for the difference in length between intraday and overnight periods.

Panel A. S&P500 index returns

	Mean	Std. Dev.	Skewness	Ex. Kurt.	5%	50%	95%
Intraday	0.00%	0.009	-0.264	14.375	-1.35%	0.05%	1.14%
Overnight	0.01%	0.006	-0.055	18.970	-0.92%	0.03%	0.81%

Panel B. Equity returns

	Mean	Std. Dev.	Skewness	Ex. Kurt.	5%	50%	95%
Intraday	0.00%	0.031	0.569	20.314	-4.25%	-0.05%	4.35%
Overnight	0.06%	0.021	1.616	61.836	-2.55%	0.02%	2.77%

Table 3 S&P index option returns during intraday sub-periods

Each trading day is divided into five equally long sub-periods. Options are delta-hedged at the start of each sub-period. "Total" column for intraday returns reports the cumulative return over all intraday sub-periods. Returns are in percentage points per day; e.g., a 0.28% daily return for index options intraday. "Excl . Weekend" column reports overnight returns excluding weekends (Friday close to Monday open). Right panel reports t-statistics that are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation. Table A.2 in the appendix reports similar results for the equity option returns.

		Return Average, %								T-statistics							
		Intraday Sub-period						Overnight		Intraday Sub-period						Overnight	
		1st	2nd	3rd	4th	5th	**Total**	**Total**	Excl. Week -end	1st	2nd	3rd	4th	5th	**Total**	**Total**	Excl. Week-end
All	All Deltas	-0.04	-0.02	-0.02	0.16	0.19	0.28	-1.04	-0.80	-0.8	-0.4	-0.6	4.3	3.7	2.6	-12.0	-9.4
	0.1 < |Δ| < 0.25	-0.17	-0.06	-0.05	0.26	0.27	0.27	-1.74	-1.40	-2.0	-0.9	-1.0	4.2	3.3	1.6	-14.1	-11.5
	0.25 < |Δ| < 0.5	-0.01	-0.02	0.00	0.15	0.21	0.31	-0.89	-0.73	-0.3	-0.5	0.2	4.4	3.8	3.2	-12.9	-10.2
	0.5 < |Δ| < 0.75	0.00	-0.01	0.00	0.08	0.09	0.15	-0.53	-0.44	0.1	-0.7	-0.2	4.9	4.6	3.4	-13.9	-11.8
	0.75 < |Δ| < 0.9	-0.01	0.01	-0.01	0.02	0.05	0.07	-0.22	-0.20	-0.8	1.3	-0.8	3.2	4.9	3.4	-11.2	-9.9
Puts	All Deltas	-0.06	-0.03	0.00	0.13	0.21	0.24	-0.90	-0.72	-1.3	-0.8	0.2	4.0	3.6	2.3	-10.5	-9.1
	0.1 < |Δ| < 0.25	-0.21	-0.06	0.00	0.21	0.25	0.20	-1.34	-1.11	-3.0	-1.1	0.0	3.9	3.4	1.3	-11.3	-10.8
	0.25 < |Δ| < 0.5	-0.01	-0.02	0.01	0.11	0.17	0.23	-0.83	-0.67	-0.2	-0.7	0.4	3.7	3.6	2.9	-13.0	-11.3
	0.5 < |Δ| < 0.75	0.02	-0.01	-0.01	0.09	0.11	0.18	-0.61	-0.48	0.9	-0.5	-0.8	4.6	4.7	3.8	-13.3	-10.5
	0.75 < |Δ| < 0.9	0.02	0.02	-0.02	0.04	0.07	0.14	-0.22	-0.16	1.2	1.8	-1.6	3.3	4.8	5.0	-6.5	-4.4
Calls	All Deltas	-0.03	-0.01	-0.04	0.16	0.21	0.28	-1.17	-0.95	-0.5	-0.3	-1.1	4.0	3.5	2.4	-12.6	-9.9
	0.1 < |Δ| < 0.25	-0.08	-0.04	-0.10	0.38	0.31	0.46	-2.23	-1.85	-0.7	-0.5	-1.4	4.2	2.7	2.0	-13.4	-10.5
	0.25 < |Δ| < 0.5	-0.01	0.00	0.00	0.19	0.22	0.39	-1.05	-0.89	-0.1	-0.1	0.0	4.6	3.9	3.5	-12.7	-10.0
	0.5 < |Δ| < 0.75	0.00	0.00	0.01	0.08	0.09	0.14	-0.50	-0.44	0.0	-0.2	0.5	4.7	4.3	3.3	-12.4	-10.4
	0.75 < |Δ| < 0.9	-0.01	0.01	0.01	0.03	0.04	0.08	-0.21	-0.19	-0.7	1.1	1.0	2.9	3.3	3.4	-8.2	-6.8

Table 4 Day and night S&P 500 index option returns by year

Returns are in percentage points per day; e.g., "0.11" means 0.11% daily return. Intraday period is divided into five equally long sub-periods. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

Year	Average Returns, %								T-statistics		
	Intraday Sub-period						Night	Diff.	Day	Night	Diff.
	1st	2nd	3rd	4th	5th	Total	Total	Day - Night	Total	Total	Day - Night
2004	-0.29	-0.06	-0.07	0.08	0.21	-0.13	-1.1	0.97	-0.6	-13.7	4.4
2005	-0.16	-0.08	-0.06	0.15	0.22	0.08	-1.13	1.20	0.4	-12.6	5.6
2006	-0.03	-0.03	0.1	0.04	0.11	0.2	-0.98	1.15	0.9	-12.3	4.7
2007	-0.22	-0.16	0.18	0.33	0.32	0.48	-0.78	1.38	1.6	-3.5	4.0
2008	-0.1	0.27	0.17	0.4	0.92	1.59	-0.77	1.51	2.5	-1.3	2.8
2009	0.05	0.02	-0.1	-0.15	0.07	-0.11	-1.13	0.99	-0.5	-6.9	3.2
2010	0.00	-0.11	-0.12	0.13	0.06	-0.05	-1.07	0.92	-0.2	-4.8	2.4
2011	0.03	0.15	-0.06	0.24	0.15	0.51	-1.07	1.52	1.5	-3.8	3.3
2012	0.16	-0.11	-0.2	0.16	-0.23	-0.21	-1.12	0.89	-0.8	-4.6	2.6
2013	0.57	-0.11	-0.03	0.16	-0.05	0.6	-1.66	2.23	0.9	-4.4	2.5

Table 5 S&P 500 index option returns double-sorted by moneyness and time-to-expiration

Moneyness is measured as absolute option delta. Maturity is measured as the number of trading days before option expiration. Returns are in percentage points per day; e.g., a 0.73% daily return for short-term index options intraday. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

Double-sorted by Moneyness (|Δ|) and Maturity (Days)	**Average Returns, %**					**T-statistics**				
	4-15	16-53	54-118	119-252	253+	4-15	16-53	54-118	119-252	253+
Intraday:										
All Deltas	0.73	0.29	0.16	0.16	0.21	3.1	2.4	1.8	2.6	3.1
0.1 < |Δ| < 0.25	0.75	0.38	0.14	0.16	0.18	1.7	1.9	1.0	1.7	2.1
0.25 < |Δ| < 0.5	0.91	0.27	0.12	0.17	0.16	3.5	2.6	1.8	3.4	3.4
0.5 < |Δ| < 0.75	0.36	0.17	0.09	0.10	0.10	3.3	3.3	2.4	3.2	2.4
0.75 < |Δ| < 0.9	0.16	0.06	0.03	0.06	0.04	3.6	2.6	1.4	2.5	0.8
Overnight:										
All Deltas	-2.62	-1.00	-0.47	-0.29	-0.22	-15.6	-12.1	-8.7	-8.4	-6.5
0.1 < |Δ| < 0.25	-5.36	-1.68	-0.72	-0.44	-0.28	-16.3	-13.5	-9.3	-8.5	-5.5
0.25 < |Δ| < 0.5	-2.81	-0.90	-0.43	-0.30	-0.22	-15.2	-12.7	-10.7	-10.4	-8.1
0.5 < |Δ| < 0.75	-1.32	-0.48	-0.25	-0.16	-0.12	-15.3	-13.6	-9.7	-4.9	-3.7
0.75 < |Δ| < 0.9	-0.37	-0.17	-0.07	0.03	-0.07	-9.0	-8.9	-3.0	0.4	-1.3

Table 6 Panel A Portfolio sorts for S&P 500 index option returns

Time series of S&P index option returns for overnight and intraday periods are sorted into four equally weighted portfolios. Option liquidity is measured as the option effective bid-ask spread. The AAII Investor Sentiment Survey measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market. "BW Sentiment" is Baker and Wurgler (2006) index of investor sentiment. Returns are in percentage points per day. The t-statistics are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

VIX Index	Intraday	Overnight	Diff	t-stat
Low, 1	-0.28	-0.86	0.58	4.9
2	-0.02	-1.03	1.02	5.3
3	0.08	-1.07	1.15	5.0
High, 4	0.97	-1.14	2.12	6.9
H - L	-1.26	0.28		
t-stat	-5.3	1.2		

LIBOR	Intraday	Overnight	Diff	t-stat
Low, 1	0.12	-1.26	1.38	6.3
2	0.05	-0.98	1.03	4.4
3	0.25	-0.94	1.18	5.0
High, 4	0.33	-0.91	1.24	6.2
H - L	-0.21	-0.36		
t-stat	-0.9	-2.2		

TED Spread	Intraday	Overnight	Diff	t-stat
Low, 1	0.20	-1.26	1.46	6.8
2	0.01	-0.93	0.94	4.2
3	0.17	-1.01	1.18	6.3
High, 4	0.42	-0.93	1.34	4.9
H - L	-0.22	-0.34		
t-stat	-0.8	-1.5		

Option Liquidity	Intraday	Overnight	Diff	t-stat
Low, 1	-0.01	-1.05	1.05	6.0
2	0.04	-1.04	1.08	6.5
3	0.15	-1.07	1.22	6.1
High, 4	0.57	-0.94	1.51	4.8
H - L	-0.58	-0.11		
t-stat	-2.1	-0.5		

AAII Sentiment	Intraday	Overnight	Diff	t-stat
Low, 1	0.66	-1.13	1.79	6.7
2	0.02	-1.04	1.06	4.8
3	0.20	-1.12	1.32	6.1
High, 4	-0.14	-0.82	0.69	3.9
H - L	0.80	-0.30		
t-stat	3.4	-1.4		

BW Sentiment	Intraday	Overnight	Diff	t-stat
Low, 1	0.08	-1.23	1.30	6.6
2	-0.27	-0.96	0.69	3.2
3	0.21	-1.09	1.30	6.8
High, 4	0.70	-0.68	1.38	4.1
H - L	-0.62	-0.54		
t-stat	-2.1	-2.1		

Table 6 Panel B Portfolio sorts for S&P 500 index option returns based on tail risk measures

Time series of S&P index option returns for overnight and intraday periods are sorted into four equally weighted portfolios based on measures of tail risk. *KJ* is the tail risk measure proposed by Kelly and Jiang (2014). *DK* is the jump tail risk measure introduced by Du and Kapadia (2012). Returns are in percentage points per day. The t-statistics are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

KJ Measure	Intraday	Overnight	Diff	t-stat
Low, 1	-0.07	-1.13	1.06	5.4
2	0.51	-0.75	1.26	4.9
3	0.24	-1.00	1.24	5.8
High, 4	0.07	-1.23	1.30	6.0
H - L	0.13	-0.11		
t-stat	0.6	-0.6		

DK Measure	Intraday	Overnight	Diff	t-stat
Low, 1	0.18	-0.91	1.09	6.5
2	0.22	-1.02	1.23	6.0
3	0.25	-0.91	1.16	4.5
High, 4	0.13	-1.10	1.24	4.2
H - L	-0.04	-0.19		
t-stat	-0.2	-0.8		

Table 7 Intraday patterns in option order imbalance

Order imbalance is computed as the difference between the number of buyer- and seller-initiated trades divided by the total number of trades. We report an average over all trading days for a given category (such as index puts). A trading day is divided into five equal sub-periods. For equity options, imbalance is equally-weighted across stocks on a given day. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation. Order imbalances are in percentage points; e.g., investors on average purchase index puts with a daily imbalance of 3.2%. That is, out of 100 trades about 51.6 are initiated by buyers and 48.4 by sellers. Thus, order imbalances are quite balanced for all categories.

	Average Order Imbalance, %						**T-statistics**					
	1st	2nd	3rd	4th	5th	**Total**	1st	2nd	3rd	4th	5th	**Total**
S&P Options												
Puts	1.8	2.3	2.9	3.5	4.9	3.2	6.0	7.2	8.6	11.3	17.4	16.1
Calls	0.1	0.1	0.6	1.2	1.9	0.9	0.4	0.3	1.7	3.6	6.7	4.5
Equity Options												
Puts	-1.2	-1.9	-1.7	-1.1	-0.6	-1.7	-9.8	-14.3	-13.0	-7.8	-4.8	-14.1
Calls	-3.9	-5.3	-4.8	-4.7	-3.6	-5.5	-30.3	-37.5	-36.4	-33.8	-28.6	-41.4

Table 8 Explaining the day-night option returns with the day-night volatility ratio

In this table, we explore how day and night option returns vary across stocks depending on the day-night volatility ratio. The first two columns report separate Fama-MacBeth regressions for day and night option returns on just the intercept. Thus, the intercept coefficients match the day-night return asymmetry documented in Table 1 Panel B (i.e., 0.1% and -0.4% per day and night periods respectively). Trying to explain these intercepts/returns, return regressions in the next two columns control for just the day-night volatility ratio. For the volatility ratio, we first compute intraday (overnight) volatility from open-to-close (close-to-open) stock returns from preceding 60 days, and then compute their ratio. The intercept coefficients become both negative and of similar magnitude. The last two columns add several controls including absolute stock return, option bid-ask spread, option volume, option implied volatility, and volatility skew. Returns are in percentage points per day (e.g., 0.1 is 0.1% per day). T-statistics (in brackets) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation. We also confirm that the absolute value of the volatility ratio $\sigma_{day}/\sigma_{night}$ coefficients in the day and night regressions are not statistically different from each other (i.e., $0.17 \cong |-0.14|$).

	$Option\ Return_{t+1}, \%$					
	Day	Night	Day	Night	Day	Night
$Intercept$	0.1	-0.4	-0.15	-0.26	-0.06	-0.10
	(3.6)	(-18.6)	(-2.5)	(-7.7)	(-0.8)	(-1.8)
$\sigma_{day}/\sigma_{night}$			0.17	-0.14	0.18	-0.13
			(14.2)	(-12.6)	(14.1)	(-9.1)
$AbsStkRet_t$					9.6	7.2
					(22.6)	(14.4)
$OptBASpread_t$					-0.1	-0.1
					(-1.3)	(-0.4)
$ImpliedVol_t$					-0.6	-1.4
					(-9.7)	(-11.0)
$VolSkew_t$					0.2	1.5
					(1.0)	(6.7)
$OptVolume_t$					0.0	0.0
					(-1.9)	(3.0)
$Adj. R^2$ (%)	0.0	0.0	0.3	0.2	2.2	1.4

Table 9 Option returns for portfolios sorted on the day-night volatility ratio

In this table, we explore how day and night option returns vary across stocks depending on the day-night volatility ratio. We sort stocks into five portfolios based on the historical day-night volatility ration. For each portfolio, we report average volatility ratio, intraday and overnight option returns as well as the return difference with the corresponding t-statistics. For the volatility ratio, we first compute intraday (overnight) volatility from open-to-close (close-to-open) stock returns from preceding 60 days, and then compute their ratio. Also, the ratio is not adjusted for the difference in length between intraday and overnight periods (to adjust multiple by 1.64). Returns are in percentage points per day (e.g., -0.33 is -0.33% per day). T-statistics (in brackets) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

	$\frac{\sigma_{day}}{\sigma_{night}}$	Option Return, % Intraday	Overnight	Diff.	T-Stat
Low, 1	1.0	-0.33	-0.03	-0.3	-5.8
2	1.5	-0.43	0.09	-0.51	-8.7
3	1.8	-0.44	0.14	-0.58	-9.8
4	2.2	-0.47	0.19	-0.67	-11.3
High, 5	3.0	-0.52	0.26	-0.78	-13.9
High - Low		-0.19	0.29		
T-Stat		-11.2	18.4		

Table 10 Parameter choices: data vs. model

Panel A the BSM model. We adjust the standard BSM model to add the day-night volatility seasonality and report our main parameter choices here. The data moments are computed using sample of S&P500 index from January 2004 to December 2013. In the model, μ is the instantaneous return (annualized) of the underlying asset. r_f is the risk-free rate (annualized). σ is the instantaneous volatility for the asset price process, scaled to daily level. σ^{IV} is the implied volatility used to price options. We choose $\sigma^{IV} > \sigma$ to match the average daily delta-hedged option returns on S&P500 index, which is approximately -0.7%. For the day-night volatility ratio, λ, or $\sigma_{day}/\sigma_{night}$, we use a range of plausible values that spans historical variation in this ratio.

	Data	Model
μ, annual	5.08%	5.08%
σ, annual	14.88%	14.88%
r_f, annual	1.52%	1.52%
σ^{IV}, annual	-	21%

Panel B the Heston model. The panel reports key parameters of the Heston model adjusted for the day-night volatility seasonality. μ is the instantaneous drift of the return process for the underlying. r_f is the risk-free rate. For the instantaneous stochastic variance process V_t, κ is its mean-reverting speed, θ is the long-run variance, η is the volatility of volatility. γ is the price of volatility risk. ρ is the correlation between innovations in asset price and stochastic volatility.

	Data	Model	Source*
μ	5.08%	5.08%	1
r_f	1.52%	1.52%	1
κ	-	34.27	3
θ	-	2.21%	1
η	-	0.28	2
γ	-	-20.16	3
ρ	-	-0.37	2

*: 1 – from the data. 2 – parameter estimation from Broadie et al. (2007). 3 – based on Broadie et al. (2007), we adjust parameters by amplifying with same multiples to get comparable magnitude in our benchmark case when $\lambda = 1.5$ and $\lambda^{MM} = 0.61$.

Table 11 Confirming cross-sectional tests for panel of simulated option returns

This table reports Fama-MacBeth cross-sectional regressions on a panel of simulated option returns. These simulations confirm our two tests for the volatility seasonality bias. After controlling for the day-night volatility seasonality, (i) the intercept becomes negative in both day and night regressions and (ii) the coefficients for the volatility ratio have the same absolute value but differ in sign $\beta^{\lambda}_{day} = -\beta^{\lambda}_{night}$. We simulate option returns in the BSM model for a cross-section of "stocks" with the day-night volatility ratio ranging from 1 to 3, to match the 10% to 90% percentiles of the cross-sectional distribution in the data. We assume that option prices completely ignore the day-night volatility seasonality. Similar our approach in Table 8, the volatility ratio is computed in two steps. We first compute intraday (overnight) volatility from open-to-close (close-to-open) stock returns from preceding 60 days, and then compute their ratio. Panel A reports Fama-MacBeth regression of day and night option returns on the volatility ratio. T-statistics are reported in parentheses are large because we can simulate a large enough panel. The option return is reported in percentage points (e.g. -0.11%). Panel B confirms that the absolute value of the coefficients for the day-night volatility ratio are not statistically different.

Panel A

	$OptRet_{Intraday}$, %		$OptRet_{Overnight}$, %	
Constant	0.16	-0.11	-0.90	-0.63
	(15.3)	(-20.1)	(-277.1)	(-75.9)
$\lambda = \sigma_{day}/\sigma_{night}$		0.13		-0.13
		(54.1)		(-53.0)

Panel B

H_0:	$\beta^{\lambda}_{day} = -\beta^{\lambda}_{night}$
p-value:	0.82
Reject or not?	Cannot reject H_0

Table 12 Trading strategy

We compare overnight returns for SPY options with their trading costs. We follow Muravyev and Person (2015) in using the adjusted effective bid-ask spreads for two investor types. "Algo" denote option trades that are likely initiated by smart execution algorithms ("Non-Algo" are all trades excluding algo trades; their trading costs equal to the conventional effective bid-ask spread). "Combined" include all the trades, both algo and non-algo. We report results for two sub-periods – before and after the tick size for SPY options was reduced to a penny on September 28, 2007. The last column reports profits from a hypothetical trading strategy that sells and delta-hedges SPY options overnight and incurs transaction costs typical for an algo-trader.

Period	Option Overnight Returns	Trading Costs			Profits after Costs for Algos
		Non-Algo	Combined	Algo	
Pre-Penny Pilot (< Sep2007)	-0.65%	3.93%	2.25%	0.66%	-0.01%
Post-Penny Pilot (> Sep2007)	-0.64%	1.24%	0.84%	0.05%	0.60%

Internet Appendix for “Why Do Option Returns Change Sign from Day to Night?”

This Appendix reports several additional results for “Why Do Option Returns Change Sign from Day to Night?” Specifically, it includes: (a) several figures and tables that complement the main results, (b) the results for computing option returns using trade prices and for (c) straddle and unhedged option returns, (d) the details of the Black-Scholes-Merton (BSM) and Heston models with day-night volatility seasonality.

A.1 Option Returns Using Trade Prices

In this section, we show that our main result is robust to computing option returns using trade prices instead of the quote midpoints. Computing returns with the quote midpoints is a de facto standard for a good reason. Besides being supported by many microstructure models, the quote midpoint has nice empirical properties: it is intuitive, observed at every instance, and is not affected by the bid-ask spread bounce. In some markets, there is a concern about whether the bid and ask prices are tradable, but in the options market overwhelming majority of trades are executed within the bid-ask spread.[18]

The advantage of using trade prices is that these are actual transactions, and thus there is less uncertainty about tradability. Unfortunately, trade prices are obviously only observed at the time of a trade. Thus, to estimate intraday option returns with trade prices, we have to limit our sample to option contracts that traded near both open and close on a given day. A similar criterion is used for overnight returns (trade around close of the previous day and open of the current day). This requirement obviously greatly reduces the sample size, as many options trade infrequently. Also, trade prices are noisy due to the bid-ask spread bounce, as buyer-initiated (seller) trades are typically executed above (below) the fair value.

We first compare average trade prices with the quote midpoints, and then compare day and night option returns for the two approaches. Panel A of Table A.8 reports the dollar and relative differences between option trade prices and midpoints. For each trade, we compute the difference between the trade price and the pre-trade quote midpoint. We further normalize it by the quote midpoint to compute the relative difference. We do not account for the trade direction

[18] For equity options, most trades are executed either at the bid or the ask.

(like in the effective bid-ask spread) because we study the bias between two prices not transaction costs.

Both differences are slightly positive meaning that trade prices are systematically higher than quote midpoints. This is to be expected because buyer-initiated trades outnumber sells for index options. The dollar difference is 0.63 cents on average and ranges from 0.24 cents in the morning to 0.99 cents in the afternoon (average option price is about seven dollars). Similarly, the relative difference is 0.09% and ranges from 0.07% to 0.12%. Almost by construction, the price difference tracks closely the patterns in order imbalance discussed in Section 4.3 and shown in Table 7. Order imbalance is positive for index options particularly in the afternoon. Simple ad hoc calculations show that the price difference is mostly driven by positive order imbalance. Multiplying a 3% order imbalance from Table 7 by 3% typical effective bid-ask half-spread produces a 0.09% expected bias, which matches the price difference in Table A.8. Also, not the 0.05% difference in prices between morning and afternoon (0.12% minus 0.07%) is small compared to intraday option returns (0.3%). Overall, the effect of buys and sells cancel each other, and the average trade price is relatively close to the quote midpoint.

Of course, the most important test here is to compare not just prices but option returns. As both open and close trade-based prices are slightly higher than option quote midpoints, this small positive bias cancels out and produces similar option returns as the quote midpoints. We compute option returns using trades the same way as from the quotes except we only delta-hedge once intraday. The reason is that the sample of options that trade at every intraday sub-period cut-off is small, and the benefits of frequent delta-hedging are small.

Panel B of Table A.8 shows a 0.44% average intraday return and a -2.26% night return with t-statistics of 2.8 and -17.8. If anything the return magnitudes are larger than for the baseline (quote midpoint) case (0.29% and -1.04%) because the subsample of traded options overweighs short-term options, as they are traded more frequently. We find similar magnitudes for both call and put options. As for the quote midpoint case, returns are more extreme for out-of-the money options because of their higher leverage. Interestingly, overnight returns are close to zero for deep-in-the money options, perhaps because these options rarely trade. Long-term and ITM options trade rarely, while slightly OTM short-term options are the most liquid.

Overall, our main result is robust to using option trade prices instead of the quote midpoints for computing option returns. However, it is important to acknowledge that both approaches to computing option returns make an implicit assumption that the quote midpoint (trade price) is perhaps noisy but an unbiased estimate of the option fair value. The fair value can potentially be anywhere between the bid and ask prices, which could be quite far apart due to the large option bid-ask spreads. Our results in this section and other robustness tests significantly reduce but not completely eliminate this concern.

A.2 Straddle and Unhedged Option Returns

Our main return measure, the delta-hedged option returns, rely on the ability to hedge a call/put by trading in the underlying. This can raise several potential concerns. First, the timestamps could be desynchronized across the two markets leading to the put-call parity violations and other microstructure effects. Luckily, our data are synchronized up to few milliseconds as our data provider aggregates from both markets simultaneously. Second, trading in the underlying requires posting margin that may not be properly accounted in option return calculations. Finally, as the portfolio consists of options and the underlying, it could be the case that the underlying part rather than option position drives our return results.

In this section, we study two option return measures that do not require hedging in the underlying to elevate these concerns. Raw returns require no delta-hedging, while straddle returns are hedged by combining calls with corresponding puts. Raw returns are equivalent to delta-hedged returns with option delta set to zero, so that they can be computed similar to delta-hedged returns. Panel B of Table A.7 reports average raw option returns. The results look good.
Day and night option returns are 0.22% and -0.93% per day respectively with t-statistics of 2.3 and -12.1. Taking an average across calls (positive delta) and puts (negative delta) to compute returns on a given day provides implicit delta-hedging (the residual delta is small). As a result, average raw returns have similar magnitudes to the delta-hedged returns (in Table 3). Then we compute raw returns separately for calls and puts, the intraday returns are similar (0.3%), but calls have almost two times less negative returns overnight (-0.6% vs. -1.1%). This pattern is consistent with the equity risk premium being small intraday and large overnight (calls have positive delta and thus benefit from positive stock returns).

We form a straddle portfolio by combining a call with as many corresponding puts (with same strike and expiration) as to make it delta-neutral. A typical straddle portfolio includes one call and one put (on average). We then compute straddle returns the same way as raw returns r returns for a delta-hedged portfolio (i.e., no delta-hedging is done except for combining calls with puts). As reported in Panel A of Table A.7, straddle returns are similar to delta-hedged returns in Table 1 (discussed in Section 4). Day and night option returns are 0.18% and -0.85% per day respectively with t-statistics of 2.5 and -17.7. The day-night return asymmetry is observed for all moneyness categories. Finally, forming a straddle portfolio our way or not is not critical for our results because as for the raw returns there is implicit delta-hedging from averaging over call and put returns.

Overall, results for raw and straddle returns together with other robustness tests in the paper suggest that our main results are robust to delta-hedging.

A.3 BSM Model with Volatility Seasonality

In this Section, we explain the details of how we add the day-night volatility seasonality and undereaction to the standard Black-Scholes-Merton model. We first explain the basic setup for the BSM model with the volatility seasonality. The underlying price, S_t, follows a geometric Brownian motion with deterministic time-varying volatility to introduce the day-night volatility seasonality. In particular,

$$\frac{dS_t}{S_t} = \mu dt + \sigma_t dB_t,$$

where B_t is a simple Brownian motion, and σ_t is the annualized *instantaneous* volatility for the underlying. To introduce the volatility seasonality, we set $\sigma_t = \sigma_{day}$ for intraday periods, and $\sigma_t = \sigma_{night}$ for overnight periods, with $\sigma_{day} > \sigma_{night}$. Obviously, this is a minor adjustment to the classic BSM model, and option prices can be easily solved for. The European call and put option prices for the no dividend case are:

$$Call_t = S_t N(d_1) - Ke^{-r_f(T-t)} N(d_2),$$
$$Put_t = Ke^{-r_f(T-t)} N(-d_2) - S_t N(-d_1),$$

where

$$d_1 = \frac{ln\left(\frac{S_t}{K}\right) + r_f(T-t) + \frac{1}{2}[\sigma_{day}^2 (T-t)_{day} + \sigma_{night}^2 (T-t)_{night}]}{\sqrt{\sigma_{day}^2 (T-t)_{day} + \sigma_{night}^2 (T-t)_{night}}},$$

$$and, d_2 = d_1 - \sqrt{\sigma_{day}^2 (T-t)_{day} + \sigma_{night}^2 (T-t)_{night}},$$

and $N(\cdot)$ is the cumulative function of standard Gaussian distribution. $(T-t)_{day}$ is a sum of the day periods over $T-t$, in years. Similarly, $(T-t)_{night}$ is a sum of the night periods. These simple formulas collapse to the standard BSM prices if $\sigma_{day}=\sigma_{night}=\sigma$.

We choose model parameters to match key return moments of S&P 500 index and its options during our sample period (January 2004 to December 2013). In particular, we assume expected return of $\mu = 5.08\%$, volatility $\sigma = 14.88\%$, risk-free rate $r_f = 1.52\%$, and implied volatility $\sigma^{IV} = 21\%$. We initially set the day-to-night volatility ratio $= 1.5$, but also consider other plausible values. Panel A of Table 10 summarizes parameter values. The implied volatility σ^{IV} is set higher than the actual volatility σ to produce the -0.7% daily delta-hedged option return observed in the data. Higher σ^{IV} relative to σ is a common way to introduce the variance risk premium in the BSM model.

We want to discuss the relationship between instantaneous (per-hour) volatility σ and the day-night volatility ratio λ, which is computed without accounting for the length difference between day and night. The following equations outline this relationship:

$$\sigma^2 = \frac{17.5}{24}\sigma_{night}^2 + \frac{6.5}{24}\sigma_{day}^2 \tag{A.3}$$

$$\lambda = \frac{\sigma_{day}}{\sigma_{night}}\sqrt{\frac{T_{day}}{T_{night}}} = \frac{\sigma_{day}}{\sigma_{night}}\sqrt{6.5/17.5} = \frac{\sigma_{day}}{1.64 * \sigma_{night}}$$

Where night and day periods are $T_{night} = 17.5$ and $T_{day} = 6.5$ hours respectively, and σ_{day} and σ_{night} are *instantaneous* (per hour) day and night volatilities. The first equation shows that total daily variance is the sum of intraday and overnight variances (adjusting for their duration). The second equation shows how to account for the difference in day-night length then computing our version of the day-night volatility ratio. Setting volatility σ to match historical data and choosing the day-night volatility ratio (e.g., $\lambda = 1.5$), we can use the two equations about to solve for σ_{day} and σ_{night}. We simulate the model with 20-year long and 365-day in each year. The first 10% sample is treated as burn-in period and therefore, is discarded.

A.4 Heston Model with Volatility Seasonality

The Heston stochastic volatility model is a common way to introduce the negative variance risk premium. We add the volatility seasonality to the standard Heston framework. In particular, the underlying price follows,

$$\frac{dS_t}{S_t} = \mu dt + \sqrt{V_t} dB_t^1,$$

where B_t^1 is a Brownian motion with no drift. V_t is the *instantaneous* stochastic variance. The stochastic volatility process follows square-root mean-reverting process,

$$dV_t = \kappa(\theta - V_t)dt + \eta\sqrt{V_t} dB_t^2,$$

where κ is the mean-reverting speed, θ is the long-run variance, η is the volatility of volatility. B_t^2 is a standard Brownian motion with no drift. In addition, $dB_t^1 \cdot dB_t^2 = \rho dt$, where $\rho < 0$ in order to reflect the leverage effect.

In a risk-neutral world, the Heston model can be written as:

$$\frac{dS_t}{S_t} = rdt + \sqrt{V_t} dB_t^{1,Q}, and,$$

$$dV_t = [\kappa(\theta - V_t) - \gamma V_t]dt + \eta\sqrt{V_t} dB_t^{2,Q},$$

where γ is the price of volatility risk, and $\gamma < 0$ indicates a negative variance risk premium. $B_t^{1,Q}$ and $B_t^{2,Q}$ are Brownian motions under risk-neutral measure, where $dB_t^{1,Q} \cdot dB_t^{2,Q} = \rho dt$ and $\rho < 0$. We set model parameters to match historical data and Broadie et al. (2007). We summarize them in Table 10.

To introduce volatility seasonality, we make following adjustments: in particular, we treat V_t as a hidden conditional variance process with adjustments to adapt to day and night variance. The seasonality-adjusted variance, SV_t, is therefore,

$$SV_t = \begin{cases} V_t^{day} = \nu^{day} V_t \\ V_t^{night} = \nu^{night} V_t \end{cases},$$

i.e., the implementation is very similar to the BSM model. We scale instantaneous variance up during day and down during night.

$$V_t = \tfrac{17.25}{24} V_t^{night} + \tfrac{6.75}{24} V_t^{day} \tag{A.4}$$

$$\lambda = \sqrt{\frac{V_t^{day} * 6.5}{V_t^{night} * 17.5}} = \frac{1}{1.64}\sqrt{\frac{\nu^{day}}{\nu^{night}}}$$

And these equations can also be solve in reverse: $\nu^{day} = \frac{24}{6.5}\frac{\lambda^2}{1+\lambda^2}$ and $\nu^{night} = \frac{24}{17.5}\frac{1}{1+\lambda^2}$. Let's make some examples: if $\lambda = 1$, then $\nu^{day} \approx 1.85$ and $\nu^{night} \approx 0.69$. If $\lambda = 1.5$, then $\nu^{day} \approx 2.56$ and $\nu^{night} \approx 0.42$.

Figure A.1 Hypothetical example of how the difference in overnight and intraday volatilities affects option returns. If day and night volatilities are equal, then option returns are similarly negative in both periods ("Vol. Ratio = 1"). However, a more common case is when total volatility is much higher intraday than overnight ("Vol. Ratio = 2"). If the implied volatility stays the same as in the previous case, it greatly overestimates overnight volatility and understates intraday volatility, which leads to large negative overnight option returns and somewhat positive intraday returns. Option returns are proportional to the difference between realized and implied volatilities.

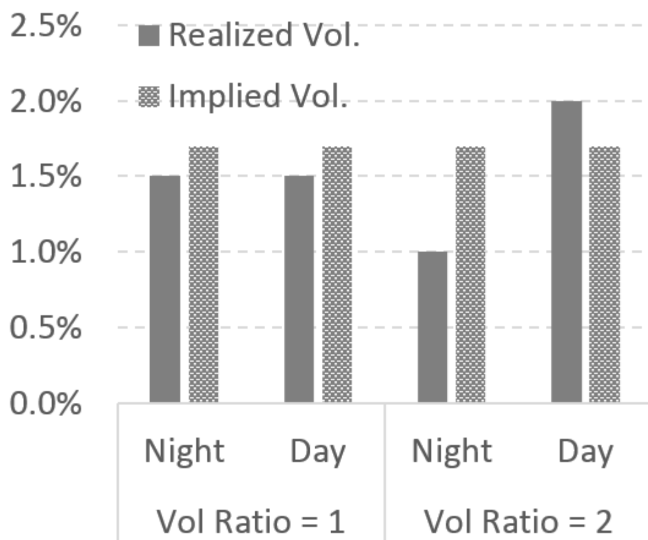

Figure A.2 Intraday returns and delta-hedging frequency.

We report how average intraday returns for S&P500 index options depend on the frequency of delta-hedging (from one time per day to five times, which is our baseline case). 95% confidence intervals are also reported.

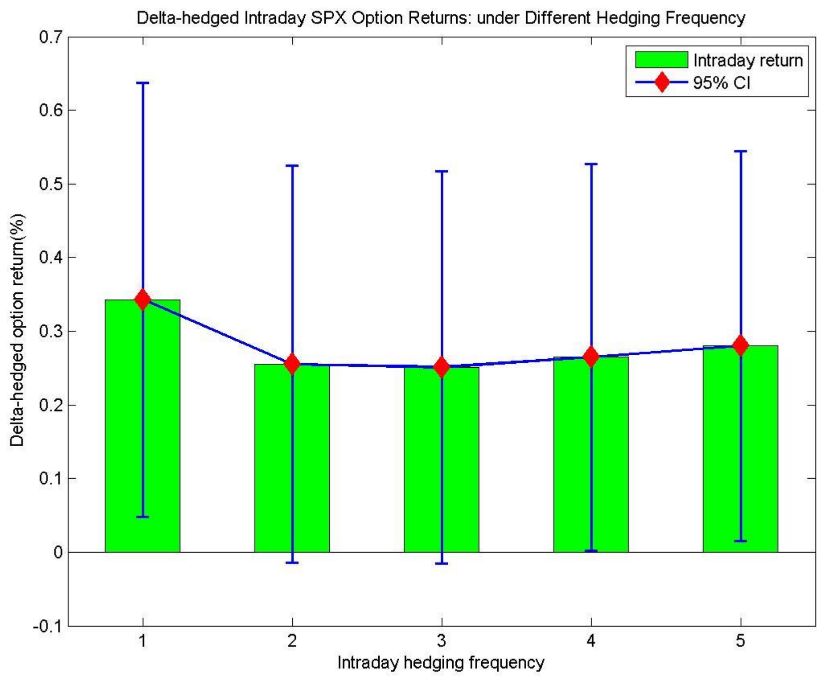

Figure A.3 Day (open-to-close) and night (close-to-open) volatility for individual stocks

We first compute the day-night volatility ratio for each stock and then plot quantiles of its distribution on each day. We report 10%, 25%, 50%, 75%, 90% quantiles and the mean (which is close to the median). Overnight volatility is computed as an average of a square root of the sum of squared close-to-open returns over the previous 60 days. We then compute a simple ratio of the day and night volatilities. Note that he ratio is not adjusted for the difference in length between intraday and overnight periods (to adjust multiple by 1.64).

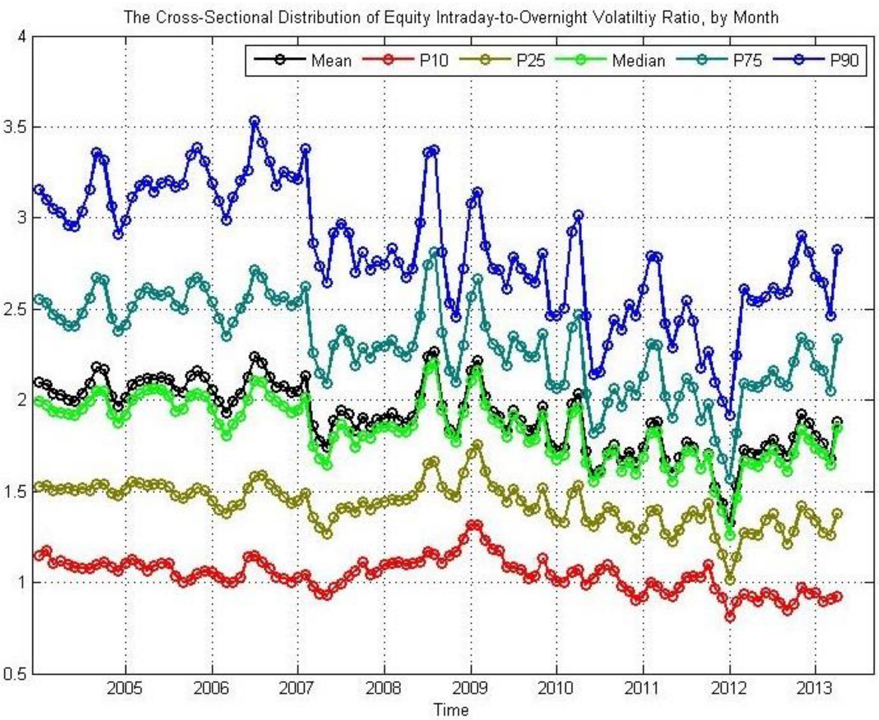

Table A.1 Day and night option returns for major ETFs

This table reports average stock volatility and option returns for overnight and intraday periods for selected ETFs. The ETFs were selected to represent major sectors and on option trading volume. Returns and volatilities are in percentage points per day. Stock volatility is measured as standard deviation of intraday or night stock returns (not annualized). The t-statistics in the last two columns are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

		Stk. Volatility, %		Opt. Ret., %		T-Stat. Opt. Ret.	
Ticker	Description	Intraday	Overnight	Intraday	Overnight	Intraday	Overnight
SPY	S&P 500	1.0	0.7	0.17	-0.49	3.1	-12.5
QQQ	NASDAQ 100	1.1	0.7	0.14	-0.39	3.0	-14.2
IWM	Russell 2000	1.4	0.8	0.15	-0.58	3.1	-18.2
DIA	Dow Jones	0.9	0.6	0.15	-0.61	2.4	-13.5
	International ETFs						
EEM	MSCI Emerg. Markets	1.5	1.5	-0.17	-0.20	-2.3	-4.2
EFA	MSCI EAFE (Europe)	1.1	1.2	-0.08	-0.05	-0.8	-0.7
FXI	China Large-Cap	1.4	1.8	-0.14	0.04	-1.9	0.6
EWZ	MSCI Brazil	1.9	1.7	-0.02	-0.17	-0.2	-2.9
	Industry ETFs						
IBB	Nasdaq Biotech.	1.2	0.8	0.23	-0.62	3.0	-7.6
XHB	S&P Homebuilders	2.2	1.4	0.09	-0.35	1.2	-8.3
XLE	Energy Sector	1.5	1.1	0.12	-0.30	2.0	-7.1
XOP	Oil&Gas Expl&Prod.	2.0	1.5	0.08	-0.32	0.6	-2.9
XLF	Financial Sector	1.8	1.2	0.06	-0.34	0.8	-8.2
XLV	Health Care Sector	0.8	0.7	0.00	-0.57	0.1	-6.7
IYR	DJ US Real Estate	2.0	1.0	0.10	-0.51	1.3	-9.2
	Commodities and IR						
USO	Oil	1.7	1.4	0.04	-0.43	0.5	-6.9
GLD	Gold	1.4	1.1	0.29	-0.70	2.6	-8.0
TLT	20+Y Treasury Bond	0.6	0.6	-0.14	-0.30	-2.1	-5.5

Table A.2 Equity option returns for intraday sub-periods

Each trading day is divided into five equally long sub-periods. Options are delta-hedged at the start of each sub-period. "Total" column for intraday returns reports the cumulative return over all sub-periods. Returns are in percentage points per day; e.g., a 0.10% daily return for index options intraday. "Excl . Weekend" column reports overnight returns excluding weekends (Friday close to Monday open). The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

		Return Average, %								**T-statistics**							
		Intraday Sub-period						**Overnight**		**Intraday Sub-period**						**Overnight**	
		1st	2nd	3rd	4th	5th	**Total**	**Total**	Excl. Week -end	1st	2nd	3rd	4th	5th	**Total**	**Total**	Excl. Week -end
All	All Deltas	0.10	-0.02	-0.04	0.00	0.05	0.10	-0.41	-0.29	7.7	-2.0	-5.7	0.1	5.7	3.0	-19.5	-13.5
	0.1 < |Δ| < 0.25	0.08	-0.05	-0.05	0.00	0.05	0.05	-0.58	-0.44	3.7	-2.7	-4.0	0.0	3.3	0.9	-16.0	-11.9
	0.25 < |Δ| < 0.5	0.14	-0.02	-0.05	0.01	0.08	0.17	-0.49	-0.35	8.5	-1.8	-5.1	1.0	6.5	4.0	-18.8	-13.2
	0.5 < |Δ| < 0.75	0.12	0.01	-0.02	0.01	0.05	0.16	-0.31	-0.21	10.8	0.8	-3.5	1.1	6.0	6.5	-19.6	-13.4
	0.75 < |Δ| < 0.9	0.09	0.03	0.00	0.01	0.03	0.16	-0.10	-0.06	14.6	5.5	0.3	2.5	4.7	11.9	-12.1	-6.9
Puts	All Deltas	0.14	0.00	-0.01	0.03	0.05	0.21	-0.49	-0.37	10.0	0.0	-0.7	2.2	4.3	6.9	-20.0	-14.6
	0.1 < |Δ| < 0.25	0.12	0.00	-0.01	0.04	0.07	0.23	-0.54	-0.41	5.5	0.0	-0.3	2.1	3.7	4.2	-15.4	-11.5
	0.25 < |Δ| < 0.5	0.17	0.01	0.00	0.04	0.07	0.29	-0.50	-0.37	10.8	0.8	-0.4	3.0	5.3	7.7	-19.1	-14.0
	0.5 < |Δ| < 0.75	0.17	0.03	0.00	0.03	0.04	0.27	-0.33	-0.25	15.4	2.9	0.5	3.9	5.1	11.7	-17.5	-12.8
	0.75 < |Δ| < 0.9	0.14	0.04	0.02	0.03	0.03	0.26	-0.12	-0.09	20.5	7.5	4.0	4.8	4.4	19.5	-10.2	-7.1
Calls	All Deltas	0.10	-0.02	-0.06	-0.01	0.06	0.07	-0.40	-0.27	4.6	-1.2	-3.5	-0.5	3.0	1.6	-16.4	-10.7
	0.1 < |Δ| < 0.25	0.22	-0.01	-0.07	0.01	0.10	0.28	-0.53	-0.35	4.9	-0.2	-2.3	0.4	2.6	2.8	-9.6	-6.1
	0.25 < |Δ| < 0.5	0.18	-0.01	-0.05	0.02	0.11	0.25	-0.47	-0.31	6.6	-0.3	-2.8	0.8	4.5	4.2	-14.6	-9.4
	0.5 < |Δ| < 0.75	0.10	0.00	-0.04	0.00	0.04	0.09	-0.29	-0.20	6.2	-0.3	-3.3	-0.3	3.2	3.1	-17.6	-11.6
	0.75 < |Δ| < 0.9	0.07	0.01	-0.01	0.00	0.01	0.07	-0.11	-0.07	7.2	1.4	-2.1	-0.2	1.6	4.8	-12.5	-7.3

Table A.3 Leverage-adjusted returns for S&P 500 index options by moneyness and time-to-expiration

Option delta hedged returns are adjusted for implied leverage as described at the end of Section 3. Moneyness is measured as absolute option delta. Maturity is measured as trading days before expiration (~252 trading days in calendar year). Returns are in percentage points per day; e.g., 0.73% daily return for short-term index options intraday. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

Moneyness (|Δ|) and Maturity (Days)	**Average Returns, %**					**T-statistics**				
	4-15	16-53	54-118	119-252	253+	4-15	16-53	54-118	119-252	253+
Intraday:										
0.1 < |Δ| < 0.25	0.023	0.015	0.007	0.013	0.031	2.0	1.6	0.8	1.3	2.4
0.25 < |Δ| < 0.5	0.025	0.014	0.013	0.019	0.025	3.3	2.4	2.2	2.8	2.9
0.5 < |Δ| < 0.75	0.015	0.010	0.008	0.009	0.014	3.5	2.7	2.0	2.0	2.3
0.75 < |Δ| < 0.9	0.006	0.003	0.002	0.007	0.014	2.5	1.5	0.9	1.6	2.0
Overnight:										
0.1 < |Δ| < 0.25	-0.102	-0.057	-0.041	-0.042	-0.053	-13.5	-9.4	-7.4	-7.3	-5.8
0.25 < |Δ| < 0.5	-0.063	-0.042	-0.033	-0.033	-0.030	-12.7	-10.2	-9.5	-8.9	-5.9
0.5 < |Δ| < 0.75	-0.038	-0.026	-0.022	-0.022	-0.023	-13.2	-11.5	-8.6	-7.4	-6.0
0.75 < |Δ| < 0.9	-0.018	-0.015	-0.010	-0.006	-0.014	-10.3	-9.9	-3.6	-1.3	-1.6

Table A.4 Option returns by time-to-expiration

Maturity is measured as the number of trading days before expiration (~252 trading days in calendar year). Each trading day is divided into five equal sub-periods. "Total" column for intraday returns reports the cumulative sum of sub-period returns. Returns are in percentage points per day; e.g., a 0.73% daily return for short-term index options intraday. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

Maturity, Days	Average Returns, %							T-statistics						
	Intraday Sub-period						Overnight	Intraday						Overnight
	1st	2nd	3rd	4th	5th	**Total**	**Total**	1st	2nd	3rd	4th	5th	**Total**	**Total**
S&P Options														
4-15	0.01	0.01	-0.11	0.36	0.41	0.73	-2.62	0.1	0.1	-1.7	4.4	3.4	3.1	-15.6
16-53	-0.07	-0.05	-0.01	0.17	0.24	0.29	-1.00	-1.1	-1.1	-0.2	4.2	4.1	2.4	-12.1
54-118	-0.03	0.00	-0.01	0.10	0.10	0.16	-0.47	-0.7	0.1	-0.5	3.5	2.1	1.8	-8.7
119-252	0.02	0.02	0.01	0.07	0.08	0.16	-0.29	0.5	0.9	0.5	2.9	2.4	2.6	-8.4
253+	0.02	0.04	0.02	0.05	0.08	0.21	-0.22	0.6	1.5	0.8	2.0	2.3	3.1	-6.5
Equity Options														
4-15	0.24	-0.04	-0.13	-0.04	0.00	0.04	-1.01	7.9	-1.7	-7.8	-2.0	0.1	0.5	-18.5
16-53	0.15	-0.02	-0.05	0.01	0.07	0.17	-0.51	9.4	-1.5	-6.1	0.8	6.7	4.2	-20.4
54-118	0.09	0.00	-0.01	0.02	0.07	0.18	-0.21	7.4	0.3	-1.6	2.2	7.1	5.6	-11.5
119-252	0.06	0.00	-0.01	0.02	0.06	0.13	-0.09	5.0	0.2	-1.3	2.4	6.3	4.6	-5.8
253+	0.07	0.02	0.00	0.01	0.03	0.13	-0.05	5.7	1.8	-0.2	1.3	3.1	4.8	-3.2

Table A.5 S&P 500 index option returns double-sorted by (normalized) option Theta and Vega

This table reports intraday and overnight option returns of portfolios double sorted by option Theta and Vega. Theta is computed as $\partial C/\partial t$, and Vega is computed as $\partial C/\partial \sigma$, where C is the option price. Theta and Vega of each option are measured at the start of each period. We then independently sort options into 4 groups by Theta and Vega, with 16 portfolios in total. Option returns are reported in percentage points per day. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

Double-sorted by Theta and Vega	**Average Returns, %**					**T-statistics**				
	$Vega_{Low}$	$Vega_2$	$Vega_3$	$Vega_{High}$	$Vega_{All}$	$Vega_{Low}$	$Vega_2$	$Vega_3$	$Vega_{High}$	$Vega_{All}$
Intraday:										
$Theta_{Low}$	0.25	0.39	0.35	0.41	0.38	2.4	2.9	2.1	2.0	2.2
$Theta_2$	0.17	0.20	0.14	0.15	0.15	3.4	2.7	1.4	1.2	1.7
$Theta_3$	0.07	0.14	0.11	0.17	0.11	1.9	2.5	1.6	1.7	2.0
$Theta_{High}$	0.03	0.09	0.14	0.15	0.09	1.4	2.5	2.8	1.5	2.4
$Theta_{All}$	0.09	0.16	0.19	0.30	0.18	2.3	2.7	2.0	1.9	2.1
Overnight:										
$Theta_{Low}$	-1.11	-1.70	-1.90	-2.04	-1.92	-13.2	-16.1	-17.0	-15.0	-16.2
$Theta_2$	-0.63	-0.72	-0.74	-0.74	-0.74	-15.1	-15.1	-12.4	-8.8	-12.8
$Theta_3$	-0.34	-0.36	-0.39	-0.37	-0.38	-13.6	-10.9	-9.2	-5.6	-10.5
$Theta_{High}$	-0.12	-0.17	-0.24	-0.30	-0.17	-6.6	-7.9	-8.0	-3.7	-7.7
$Theta_{All}$	-0.46	-0.63	-0.96	-1.53	-0.92	-14.3	-10.9	-14.5	-14.5	-14.3

Table A.6 Volatility and equity risk cannot explain day-night option returns

The table reports a time series regression of S&P 5000 delta-hedged index option returns on the index returns (Panel A) and VIX futures returns (Panel B). Index and VIX futures returns are computed over exactly the same period as option returns (e.g., open-to-close for intraday). We report results separately for intraday and overnight returns. Returns are in percentage points per day; e.g., the intercept of "0.18" means a 0.18% daily abnormal alpha. T-statistics are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

Panel A: $OptRet_t = a + b * Ret_t + \epsilon_t$

	Intraday		Overnight	
	a	b	a	b
Coeff.	0.18	-2.07	-0.99	-3.33
T-stat.	2.1	-10.2	-18.4	-10.4

Panel B: $OptRet_t = a + b * Ret_t + c * VIXFutRet_t + \epsilon_t$

	Intraday			Overnight		
	a	b	c	a	b	c
Coeff.	0.24	0.08	0.92	-0.89	-1.63	0.66
T-stat.	3.2	0.5	17.3	-12.8	-2.6	5.6

Table A.7 Unhedged returns and straddle returns for S&P 500 index options

We explore the robustness of our main result by computing option returns in two alternative ways that do not require delta-hedging in the underlying. Panel A reports returns for a straddle portfolio that includes a call and as many corresponding puts (with the same strike and expiration) as to make it delta-neutral. On average, a straddle portfolio has one call and one put. Panel B reports raw option returns. I.e. returns are computed the same way as in the baseline case except no delta-hedging is done. Returns are in percentage points per day; e.g., "0.18" means a 0.18% daily return. Intraday period is divided into five equally long sub-periods. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

Panel A Straddle returns

	Return Average, %							**T-statistics**						
	Intraday Sub-periods						**Overnight**	**Intraday Sub-periods**						**Overnight**
	1st	**2nd**	**3rd**	**4th**	**5th**	**Total**	**Total**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**Total**	**Total**
All Deltas	-0.03	-0.02	-0.02	0.11	0.14	0.18	-0.85	-0.9	-0.9	-0.8	4.3	3.9	2.5	-17.7
0.1 < |Δ| < 0.25	0.03	-0.01	-0.04	0.15	0.13	0.26	-1.00	0.5	-0.2	-1.2	3.9	2.8	2.7	-14.1
0.25 < |Δ| < 0.5	0.03	0.00	-0.02	0.13	0.16	0.30	-0.91	0.7	0.0	-0.7	4.7	4.0	3.9	-16.5
0.5 < |Δ| < 0.75	-0.01	-0.02	0.00	0.10	0.11	0.19	-0.73	-0.2	-0.8	-0.1	4.5	4.0	3.1	-17.0
0.75 < |Δ| < 0.9	-0.10	-0.04	-0.02	0.12	0.13	0.09	-0.89	-3.0	-1.5	-0.8	4.3	3.8	1.2	-16.6

Panel B Unhedged returns

	Return Average, %							**T-statistics**						
	Intraday Sub-periods						**Overnight**	**Intraday Sub-periods**						**Overnight**
	1st	**2nd**	**3rd**	**4th**	**5th**	**Total**	**Total**	**1st**	**2nd**	**3rd**	**4th**	**5th**	**Total**	**Total**
All	-0.04	-0.03	-0.02	0.14	0.16	0.22	-0.93	-0.8	-0.8	-0.7	4.1	3.6	2.3	-12.1
Puts	0.13	0.05	-0.10	0.15	0.00	0.31	-1.16	0.8	0.4	-1.0	1.1	0.0	0.9	-4.6
Calls	-0.17	-0.07	0.07	0.18	0.32	0.39	-0.63	-1.2	-0.6	0.7	1.5	2.0	1.3	-3.1

Table A.8 Trade price as an alternative to the option quote midpoint

Panel A compares trade price with a quote midpoint at the time of the trade for S&P500 index options. We split every day into five equally long sub-periods. For all option trades in a given sup-period and day we compute the average dollar difference ($TP_i - Mid_i$) and relative difference $(TP_i - Mid_i)/Mid_i$ between trade price and quote midpoint. We then compute average across days. "0.0024" means 0.24 cents. Panel B reports day and night option returns computed from trade prices. For a set of options that trade around both open and close, we compute option delta hedged returns the same way as for the quote midpoints (i.e., delta-hedging, etc.). Returns are in percentage points per day; e.g., "0.44" means 0.44% daily return. Intraday period is divided into five equally long sub-periods. The t-statistics (right panel) are computed using the Newey-West

Panel A Average difference between option trade prices and the quote midpoints

	Intraday Sub-period					
	1st	**2nd**	**3rd**	**4th**	**5th**	**Overall**
Dollar Difference, $	0.0024	0.0032	0.0067	0.0088	0.0099	0.0063
Relative Difference, %	0.07	0.07	0.08	0.10	0.12	0.09

Panel B Day and night option returns computed from option trade prices

		Return Average, %			**T-statistics**		
		Intraday	**Overnight**		**Intraday**	**Overnight**	
		Total	**Total**	Exclude Weekends	**Total**	**Total**	Exclude Weekends
All	All Deltas	0.44	-2.26	-1.82	2.8	-17.8	-14.0
	0.1 < |Δ| < 0.25	0.62	-3.84	-3.10	2.3	-18.7	-14.7
	0.25 < |Δ| < 0.5	0.43	-1.98	-1.67	3.2	-18.7	-15.5
	0.5 < |Δ| < 0.75	0.32	-0.69	-0.45	4.0	-9.8	-6.1
	0.75 < |Δ| < 0.9	0.27	-0.03	0.06	3.8	-0.3	0.4
Puts	All Deltas	0.40	-2.32	-1.96	2.6	-17.2	-14.1
Calls	All Deltas	0.48	-2.41	-1.83	2.7	-14.7	-10.7

Table A.9 S&P 500 index option returns using alternative open and close option prices

This table reports intraday and overnight option returns using alternative definitions of open and close option prices. In particular, we compute option returns using (i) 10 a.m. quote midpoint as open price, (ii) 4 p.m. as close price (index options close at 4:15p.m.), (iii) compute returns using only option bid prices and (iv) using only ask prices. Option returns are reported in percentage points per day. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

	Option Returns		T-statistics	
Option Price	**Intraday**	**Overnight**	**Intraday**	**Overnight**
Open at 10am	0.29%	-1.17%	3.4	-16.7
Close at 4pm	0.20%	-1.08%	2.3	-16.1
Option Bid	0.27%	-1.08%	2.9	-14.2
Option Ask	0.22%	-0.96%	2.4	-13.5

Table A.10 VIX futures returns

Maturity is measured in trading days to expiration. First we compute average return for all futures in a given maturity bin on a given day and then compute average return across days. Returns are in percentage points per day; e.g., "0.11" means a 0.11% daily return. Intraday period is divided into five equally long sub-periods. Overnight period is from 4:15 pm to 9:30 am. to match the options results. The t-statistics (right panel) are computed using the Newey-West (1987) adjustment for heteroskedasticity and autocorrelation.

Maturity, days	**Return Average, %**							**T-statistics**						
	Intraday Sub-periods						**Overnight**	**Intraday Sub-periods**						**Overnight**
	1st	2nd	3rd	4th	5th	**Total**	**Total**	1st	2nd	3rd	4th	5th	**Total**	**Total**
Front-month	0.06	0.03	0.00	0.01	-0.10	0.01	-0.15	1.3	1.0	0.0	0.3	-2.7	0.1	-2.6
4-15	0.11	-0.02	0.05	0.01	-0.10	0.04	-0.20	1.7	-0.5	1.1	0.3	-1.9	0.4	-2.4
16-53	0.03	0.03	-0.01	0.02	-0.01	0.06	-0.15	0.8	1.0	-0.2	1.0	-0.5	1.0	-3.3
54-118	0.00	0.03	0.01	0.03	0.02	0.08	-0.09	-0.2	1.6	0.4	1.7	1.0	2.0	-2.7
119-252	-0.05	0.00	0.00	0.02	0.05	0.02	0.04	-2.1	0.3	0.0	1.4	1.6	0.5	0.9
253+	-0.02	0.00	0.01	0.00	-0.01	-0.02	-0.03	-1.6	-0.5	0.6	0.2	-1.2	-1.1	-1.9

Informed Trades, Stock Return Predictability and the Disclosure Effect of Option Information[*]

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Abstract

Option order imbalances predict the cross-section of equity returns. We show that a large part of this predictability can be attributed as one-day announcement effect. Predictability of option order imbalances declines as forecasting horizon prolongs. In particular, we show that, the predictability of long-horizon predictability depends on the privacy of information. Public disclosure of option trades information has a crucial and negative impact on the predictability of option order imbalances. Furthermore, using identification algorithms, we can imprecisely distinguish between investor's trades and option market maker's trades and find that, the order imbalances from non-option market makers contain almost all information relevant for predicting future stock returns. Our results are consistent with theories implying that option trading volume reflects the actions of informed traders, and the action of disclosing this information can facilitate asset price movements.

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1. Introduction

The fundamental economic question of how information gets incorporated into asset prices has always been an interesting topic in information theory as well as of practical interest. This paper examines the informational content of option trading for future movements in underlying stock prices. In particular, using a unique external variation event, we examine the impact of information disclosure on the predictability of subsequent stock returns. We also examine what characteristics do option informed trades have in detail. Theoretically and practically, the embedded leverage feature of options allows capital-constrained investors, e.g. investors who cannot borrow from money market, to leverage up their positions in a very short period of time.

Our focus on the informational role of derivatives, particularly equity options, comes at a time when derivatives play an increasingly important role in financial markets. Indeed, for the past several decades, the capital markets have experienced an impressive proliferation of derivative securities, ranging from equity options to fixed-income derivatives to, more recently, credit derivatives. The view that informed investors might choose to trade derivatives because of the higher leverage offered by such instruments has long been entertained by academics (e.g., Black (1975)) and can often be found in the popular press. A formal treatment of this issue is provided by Easley, O'Hara, and Srinivas (1998), who allow the participation of informed traders in the option market to be decided endogenously in an equilibrium framework. In their model, informed investors choose to trade in both the option and the stock market—in a "pooling equilibrium" - when the leverage implicit in options is large, when the liquidity in the stock market is low, or when the overall fraction of informed traders is high.

Our main empirical methodology seek to address two main questions: first of all, we want to empirically quantify the impact of option-trading information disclosure on predictability of future stock returns in the cross-section. Second, and more interestingly, we want to identify the characteristics shared by option informed trades. In particular, we want to show that only order imbalance signals constructed from informed trades poor can predict future stock price movements. Option order imbalance construct from liquidity-trades pool add little value in predicting future stock returns.

In Section 3, using a unique dataset from ISE, which contains trades initiation and direction information, as well as some client information, we empirically quantify the impact of option-trading information disclosure on the predictability of future stock returns. Specifically, we construct multiple order imbalance predictors, for example, the Pan and Poteshman (2006) put-call ratio, as well as open-buy call (or open-buy put) order imbalance measures, and empirically test their stock return predictability from 2005 to 2013. The empirical results show that, across over all sample, the predictability coefficient, beta, is statistically significant across the sample for one-day forecasting horizon. Only put-call ratio and open-buy put ratio can predict future stock returns at 1-week (skipping 1-day) and 1-month (skipping1-day) horizon. In particular, as illustrated in Figure 1 Panel A, we show that the stock return predictability of put-call measure is the strongest for 1-day horizon (similar patterns are also true for other order imbalance predictors). Overall, we still find predictability of measure for 1-week and 1-month horizon: however, this predictability concentrates in the pre-disclosure period. Ever since ISE started to sell Open/Close profile to investors in late 2007, the middle to long horizon predictability has weakened. In Table 1 and Table 2, we formally test the effect of ISE disclosure by introducing dummy variables representing different sub-periods. Our findings are broadly consistent with what Pan and Poteshman (2006) mentioned in their paper: only private option volume signal predict future stock returns. Under our setting, the ISE disclosure provides us with a perfect experiment scenario to study how option volume predicts future stock returns when private signal becomes public.

Since, we do find out evidence in supporting of informed trades in equity option market. Next, we want to examine what characteristics are commonly shared by option informed trades. Practically, we can treat this problem as how to identify informed trades from a big pool consists of liquidity trades/hedging-based trades, informed trades that seek to speculate on underlying stock price movement, and noisy trades. Given the high transaction costs and bid-ask spread in trading options, the noisy trade portion only account for a small fraction of total trading volume, which is in sharp contrast from stock market. Therefore, our main research problem is to separate informed trades from liquidity-based option trades. To achieve this purpose, we make few very critical assumptions: first of all, we assume that the option trades are primarily consist of liquidity/hedging trades, informed trades that seek to bet on future stock movements, and noisy trades. Second, we assume that liquidity-based trades are mostly initiated by option market makers and for this type of trades, reducing the effective costs of trading options is the main purpose. In other words, liquidity traders only care about temporary option price movements. Meanwhile, informed traders who seek to bet on underlying stock price movements are more concerned about long-term option price movements caused by movements in underlying stock prices. This implicit hypothesis gives critical empirical implications: we can try to time the short-term option market to reduce the effective costs of trading options, which we call it execution-timing algorithms

In Section 4, we take advantage of the mega minute-level data from Nanex and implement our classification algorithms. . The direction of each option transaction is determined according to the Lee and Ready (1991) algorithm. Over a fixed time interval (say, a day), the volume of the signed option transactions can be aggregated to generate an order flow measure for each option contract. Based on our execution-timing algorithm, we can *imprecisely* divide the total option trades pool into two sup-groups: one group contains liquidity trades, noisy trades, and few informed trades, another pool only contains informed trades, and noisy trades. Given this separation, we can indirectly test the validity of our implicit assumptions described above. First and foremost, we want to demonstrate that our execution-timing based order imbalance measures are efficient in predicting future cross-sectional stock returns, both in short and long horizon. And we also show that the order imbalance predictors constructed from liquidity pool are not as efficient. In Table 3, we have shown that the order imbalance predictors constructed from informed-trades pool are strong predictors of future price movements, not only for next day, but also for 1-week (skipping 1-day), and 1-month (skipping 1-day) horizon. As reported in Table 4 Panel A, the High-Low $BBPC$ (BBC/C, or BBP/P) strategy generates -8.39 (4.07, or -3.51) basis points FF3 alpha per day, equivalent to -23.5% (10.8%, or -9.25%) per annum.

The rest of the article is organized as follows. Section 2 reviews the literature on the price impact of option trading. In Section 3, we discuss the datasets and describe the sample construction in detail. In Section 4, we empirically examine the negative information disclosure effect of option trades information on the predictability of future underlying stock price movements. In Section 5, we first describe our execution-timing algorithms and theoretical assumptions in detail. Then we test our hypothesis using trade-level data from Nanex. Section 6 concludes the findings.

2. Literature Review and Motivations

Microstructure theories such as Ho and Stoll (1981), Glosten and Milgrom (1985), Kyle (1985), and Easley and O'Hara (1987) suggest that a stock's order flow affects its price and that , in particular, transactions initiated by buyers (sellers) cause the stock prices to move up (down). The empirical evidence that supports this prediction exists both at the market level (Chordia, Roll, and Subrahmanyam, 2002) and in the cross-section of stocks (Chordia and Subrahmanyam, 2004). The stock options market provides an alternative venue for gaining stock exposure. For example, Easley, O'Hara, and Srinivas (1998) and Pan and Poteshman (2006) show that options order flow also predicts the underlying stock returns. This paper examines the interaction between option transactions and the underlying stock transactions and how this interaction affects the predictability of stock returns. In addition, the stock options market also provides investors with valuable approaches to managing volatility. In particular, N, Pan and Poteshman (2008) investigates informed trading on stock volatility in the option market and they show that the non-market maker net demand for volatility is quite informative about about the future realized volatility of underlying stocks.

Derivative trading can convey important information in a market with information asymmetry. Black (1975) first notes the possibility that informed traders could use the options market as an alternative trading venue because option contracts provide higher leverage. Biais and Hillion (1994) examine the impact from the introduction of options and find that informed traders' profits can either increase or decrease depending on the type of liquidity orders. Focusing on how private information gets incorporated into security prices, Easley, O'Hara, and Srinivas (1998) formalize a two-market microstructure model in which informed traders choose to trade in the stock or options markets. The authors show that a pooling equilibrium exists in which informed traders trade in both markets when the leverage and liquidity of the options are sufficiently high. They further argue that because the availability of multiple option contracts presents difficult learning problems for uninformed traders, option contracts can be more attractive to informed traders. If informed traders trade in the options market, the options order flow can contain information about fundamental values of the underlying stocks.

The theoretical discussion on the feedback effect from options has motivated many empirical studies on the lead-lag relation between the two markets. A group of researchers focus on the relation between the actual stock prices and the implied stock prices from options. Early studies such as Manaster and Rendleman (1982) and Bhattacharya (1987) find that the options market leads the stock market in price discovery. However, more evidence points in the opposite direction. For example, Chakravarty, Gulen, and Mayhew (2004) find that the information share of option quotes is less than 20% on average. Holowczak, Simaan, and Wu (2006) show that the information share of options even decreases over time, and they argue that this decrease is because of the prevailing use of computers for the automatic updating of quotes in the options market. In a recent study, Muravyev, Pearson, and Broussard (2013) find that option quotes, but not stock quotes, adjust themselves to eliminate arbitrage opportunities across the two markets, and they conclude that the options market does not play a role in price discovery. Another strand of empirical research directly investigates the options order flow. Many studies find that this order flow predicts future stock returns in time series regressions for a small group of stocks, for example, Easley, O'Hara, and Srinivas (1998), Poteshman (2006), Dong and Sinha (2011), and Holowczak, Hu, and Wu (2014).

Pan and Poteshman (2006) investigate the information content of the options order flow in the cross-section of stocks. Using a unique dataset, these authors construct volume ratios of put and call options from buyers opening new positions. They find that the open-buy put-call ratio negatively predicts returns and that there turn predictability lasts over three weeks. However, as we will argue in this paper, the predictability of put-call ratio is really coming from the privacy of signals. Once these order information get disclosed, stock prices react to it in a very short period of time.

Chan, Chung, and Fong (2002) investigate the informational role of order flows and quote revisions in the two markets. They find that the options order flow does not have a pricing effect but the stock order flow does. Cao, Chen, and Griffin (2005) examine order flow information around mergers and acquisitions. Their results suggest that the options volume imbalance becomes significantly informative about future stock prices right before merger announcements but remains silent during normal periods.

3. Data and Sample Construction

In this section, we discuss the data and empirical methodology used in this paper. We obtained stock prices from CRSP, and firm fundamentals from Compustat. The option prices and trades information come from two different sources: International Securities Exchange[1] (ISE) and Nanex. The ISE database contains daily option trades information from ISE: in particular, it provides daily buy and sell trading volume for each option series traded at the ISE, disaggregated by whether the trades open new option positions or close existing positions. Trades on reported on ISE Open/Close profile represents about 20% to 30% of the total trading volume in equity and ETF options during our sample period spanning from May 2005 to December 2012. The other

[1] A detailed description of the ISE data is available at http://www.ise.com/market-data/products/put-call-data/ise-open-close-trade-profile/.

data source is from Nanex, a firm specializing in providing high-frequency stock and option quotes and trades data. The original data come from standard data aggregators: OPRA for options and SIP for equities (e.g., TAQ data also use SIP). The data include intraday quoted bid and ask prices at one-minute frequency for both options and the underlying equities for the sample period from January 2004 to December 2015. For options, we also observe best bid and offer (BBO) from all option exchanges. Advantages of this second dataset are that it covers a longer time period, including the period after the Penny Pilot when the options market minimum tick size decreased to one cent per share, and for each date includes data on the full cross-section of options that traded on that date. Timestamps are synchronized across markets. To reduce dataset size, only option contracts with at least one trade on a given day are included. Even given these constraints intended to reduce the size, the compressed data are still require more than fifteen terabytes of storage. For either datasets, because we focus on the ability of option order imbalances predict cross section of stock returns, we exclude index and foreign exchange options from analysis.

The ISE data include volumes due to trades of both firm proprietary traders and public customers. For each option series and trader type or trade size bucket, the option trading volume data are broken down into four categories: volume from buy orders that open new purchased positions (open buy volume), volume from sell orders that open new written positions (open sell volume), volume from buy orders that close existing written positions (close buy volume), and volume from sell orders that close existing purchased positions (close sell volume). Part of our analyses, which is built on this ISE dataset, combines the volumes from the different trader types and trade size buckets. For each underlying stock and volume type we aggregate the volume for the different call and put series, yielding four call volumes and four put volumes for each underlying stock. Considering the different characteristics, i.e., open/close, buy/sell, and call/put, we have eight categories of options volume, which are open buy call (OBC), open sell call (OSC), close buy call (CBC), close sell call (CSC), open buy put (OBP), open sell put (OSP), close buy put (CBP), and close sell put (CSP).

For the Nanex dataset, we compute option order imbalances using option trades as well as BBO quoted prices preceding a trade. First, the quote rule is applied to trade and NBBO (National Best Bid and Offer) option prices to determine whether a trade is buyer or seller-initiated; if a trade is at the NBBO quote midpoint, we apply the quote rule to the quoted bid and ask prices from the exchange that reported the trade.

We also want to briefly comment on the options market structure. The U.S. options market clearly resembles the U.S. equity market with some distinct differences. Equity options are typically cross-listed across multiple exchanges, most of which are fully electronic, and NBBO rule is enforced. Anybody can post limit or market orders, but market-makers are obliged to provide continuous two-sided quotes. All major brokers provide real-time option prices to their (retail) clients similarly to stock information. S&P500 index options are somewhat special because one exchange, CBOE, has exclusive rights to trade SPX options, and a large fraction of trading is still done manually. Even for SPX options, there are continuous bid and ask prices that investors can trade against (See Muravyev (2016) for further details).

In Section 3, we take advantage of the unique client information obtained from ISE dataset to specifically test the information content contained in open-buy/open-sell type option order imbalances. In Section 4, we rely on the trade-level information for every single-name stock as well as ETFs to separate option market maker’s liquidity trades from superior informed trades with future stock price information.

4. ISE Open/Close Order Imbalances and the Cross-Section of Stock Returns

Literature, e.g. Pan and Poteshman (2006), have shown that option trading volume contains valuable information about future stock price movements. In this section, we use ISE Open/Close profile to test and validate main empirical results documented by Pan and Poteshman (2006) and Pearson et al. (2016). We briefly discuss results in this section and further explore the public disclosure effect on the predictability of those well-documented order imbalance measures since ISE began to sell this Open/Close profile in November 2007. Henceforth, it is interesting to investigate whether this public disclosure event affects stock return predictability. As illustrated in the paper by Pan and Poteshman (2006), the open-buy put-call ratio measure is defined as,

$$PC = \frac{OBP}{OBP + OBC + 5},$$

where OBC (OBP) is the open-buy call (open-buy put) volume. The aggregation of OBC (or OBP) is described in detail by Pearson et al. (2016). We add a small number 5 in the denominator to avoid special case: $OBP + OBC = 0$. Differing from what Pan and Poteshman (2006) used in their paper, since we don't have CBOE data, we use ISE data to examine the stock return predictability. By theory, if option trades are informative, we should also observe cross-sectional predictability in the ISE dataset.

Slightly different from what Pearson et al. (2016) used in their paper, we construct open-buy call and open-buy put order imbalance measures as follows:

$$OBC/C = \frac{OBC}{TC + 5}, and\ OBP/P = \frac{OBP}{TP + 5},$$

where $TC = OBC + OSC + CBC + CSC$ represents total call volume, and $TP = OBP + OSP + CBP + CSP$ stands for total put volume. In the original paper by Pearson et al. (2016), they normalize OBC (or OBP) by stock volume. We find that normalizing by option volume delivers a better signal when predicting cross-section of stock returns, especially for middle to long horizon. Therefore, we use normalizing by option volume as our benchmark case.

4.1. The Cross-Sectional Stock Return Predictability

Whether option trades are informative is always a hot issue, papers, such as Pan and Poteshman (2006), Hu (2014) and Pearson et al. (2016), have shown empirical evidence that option order imbalance is informative and can predict future stock returns. However, those studies do not discuss how long can this predictability sustains. Notwithstanding this deficiency, all studies generally do agree that the next day predictability is the strongest, which we would like to call it announcement effect. If we purge out this next-day announcement effect, order imbalance measures from previously mentioned papers are not so satisfactory: Pan and Poteshman (2006) put-call ratio still works due to data limitations (at the time of the study, CBOE does not sell this open/close profile to investors). Besides Pan's work, Hu's (2014) stock order imbalance measure loses predictability and no further are provided in Pearson et al. (2016). Henceforth, in this part, we provide analysis on the cross-sectional predictability of Pan (2016) and Pearson (2016) measures at different forecasting horizon: 1-day ahead, 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day). Notice that for 1-week and 1-month horizon, we intentionally exclude the next-day to avoid strong announcement effect. Without causing confusion, we will use 1-week and 1-month instead of 1-week ahead (but skipping 1-day) and 1-month ahead (but skipping 1-day) for simplicity.

We examine the cross-sectional predictability, as well as disclosure effect using Fama-MacBeth (1973) regressions. In Figure 1 Panel A, we plot the time-series of coefficients of Pan (2006) put-call measure, PC. To smooth the figure, we take 100-day moving average. As illustrated in Figure 1 Panel A, we show that the stock return predictability of PC measure is the strongest for 1-day horizon. Overall, we still find predictability of PC measure for 1-week and 1-month horizon: however, this predictability concentrates in the pre-disclosure period. Ever since ISE started to sell Open/Close profile to investors in November 2007, the middle to long horizon predictability has weakened. We will formally test this public disclosure effect in the subsequent sections.

As reported in Table 1 Model 1 column, the Fama-MacBeth (1973) estimate of PC for 1-day horizon is -0.098 with a t-stat value of -8.25. And the significance of this predictability gradually declines as forecasting horizon extends: the t-stat value for 1-week horizon is -3.4 and for 1-month horizon is -2.56. Given these empirical results, we can conclude that the Pan and Poteshman (2006) order imbalance measure, PC, does predict cross-section of stock return at different horizons, though the degree of predictability varies.

We also examine the predictability of Pearson et al. (2016) order imbalance measures, OBC/C and OBP/P. In Figure 2 Panel A.1 and Panel A.2, we report time series of coefficients of OBC/C and OBP/P, respectively. As illustrated in the figure, both OBC/C and OBP/P display strong 1-day announcement effect: stocks with higher OBC/C (OBP/P) tend to perform better (worse) next day. The announcement effect is weakened as ISE began to sell the data to investors, but still remains and is nontrivial. In contrast, similar to what we find in the put-call ratio, PC, case, the 1-week and 1-month predictability concentrates in pre-disclosure period. After the disclosure date, the middle to long term predictability for OBC/C and OBP/P gradually dies away (2008 and 2009 are still Financial Crisis period, in which case data behaves differently as we can see from the figure).

In Table 2 Panel A and Panel B, we report Fama-MacBeth regression results for OBC/C and OBP/P at different forecasting horizons, respectively. Besides what we observe in Figure 2 Panel A, open-put order imbalance measure, OBP/P, seems to be a better signal at predicting stock returns than open-call order imbalance measure OBC/C. Evidence suggests option investors normally do not use calls as a long-term investment tool.

Using ISE dataset, we have demonstrated short-term stock return predictability for Pan (2006) and Pearson (2016) order imbalance measures. Besides, we also provide evidence indicating weaker predictability as forecasting horizon extends. During Financial Crisis period, we find spikes in predictability at all order imbalance measures, we argue that this phenomenon is due to capital constraints: investors are unable to leverage up using money market tools so they in turn use option as a tool for embedded leverage. Furthermore, we show significant decline in predictability at all horizons due to disclosure event by ISE. The ISE disclosure effect is going to be discussed in the next section.

4.2. The ISE Disclosure Effect on the Predictability of Option Order Imbalances

As we mention earlier in the paper, the International Securities Exchange, or ISE, started to sell this Open/Close profile to investors from November 2007. Furthermore, Pan and Poteshman (2006) document that the predictability of put-call order imbalance measure merely exists if they use private signal: at that time, the CBOE Open/Close profile is undisclosed. Therefore, it is reasonable to wonder whether the disclosure event could weaken the predictability of documented option order imbalances since those measures proposed by Pan and Poteshman (2006) and Pearson et al. (2016) are not private anymore.

In Figure 1 Panel B, we explore the variation trend in coefficients of PC measure from May 2005 to December 2012. In particular, we compute the average coefficient by year and corresponding 95% confidence interval. As illustrated in Figure 1 Panel B, we still have significant predictability at 1-day horizon albeit slight weaker compared with before disclosure situation. However, things start to get worse when for 1-week and 1-month forecasting horizon. If we exclude periods involving Financial Crisis (2008 and 2009), then the middle to long-term predictability almost disappears for post-2010 period, as displayed in the 2nd and 3rd sub-figure in Panel B. Similarly, we also find gradually disappearing predictability for Pearson (2016) OBC/C and OBP/P measures as illustrated in Figure 2 Panel B.1 and Panel B.2. For both OBC/C and OBP/P order imbalance measures, the 1-week and 1-month predictability almost demise after ISE started to sell its Open/Close profile data (excluding periods affected by Financial Crisis and its aftermath).

To further validate our findings in Figure 1 and Figure 2, we formally test the effect of ISE disclosure by introducing dummy variables and reported regression results in Table 1 and

Table 2. To examine the effect associated with public disclosure, which essentially creates a perfect exogenous shock for identification, we create several time dummies: $D(date \geq 200712)$ equals 1 if date is greater than or equal to 12/2007; otherwise equals 0. Following same logic, we also define $D(date \geq 200712$ & $date \leq 200912)$ and $D(date \geq 201001)$. From Table 1 and Table 3 column Model 3, we find that whatever order imbalance measure we are using, either Pan (2006) PC measure or Pearson (2016) OBC/C (OBP/P) measure, the 1-week and 1-month horizon predictability decreases sharply for post-2010 period, which is particularly phenomenal for put-call ratio PC measure. Besides, the summation of constant and coefficient on $D(date \geq 201001)$ is indifferent from zero statistically.

Our findings are broadly consistent with what Pan and Poteshman (2006) mentioned in their paper: only private option volume signal predict future stock returns. Under our setting, the ISE disclosure provides us with a perfect experiment scenario to study how option volume predicts future stock returns when private signal becomes public. We can conclude that option volume does contain valuable information about future stock prices and are incorporated into asset prices as information becomes publicly available. The analysis on ISE disclosure also reveals two opposite hypothesis. The long-term predictability disappears due to either (1) option open-buy order imbalances are not informative anymore, or (2) option open-buy order imbalances are still informative, but information gets incorporated into asset prices in a faster pace since ISE started to disclose this private information. If hypothesis (2) is true, then it implies private signal, if properly constructed, can still predict long-term cross-sectional stock returns. We will investigate those two hypotheses using execution-timing methodology in the next section.

5. Execution-Timing based Order Imbalances and the Cross-Section of Stock Returns

In the option market, option market makers usually take in trades passively to clear the market. Those trades are generally not informative about underlying asset prices and are called liquidity trades. Therefore, we want to purge out those liquidity trades from market makers and collect trades from retail investors and institutional investors, who trades based on superior information. To meet this objective, we borrow ideas from Muravyev and Pearson (2016) and use their execution-timing algorithm to distinguish between market maker's trades and other trades (e.g. retail investors, institutional investors, and noisy traders) from Nanex trade-level dataset. In Eq.(3) of their paper, they define their option price predicting equation as:

$$P_{t+\tau} - P_t = \alpha_0 + \alpha_1\left(\hat{P}_t^{BSM} - P_t\right) + \alpha_2(\Delta_{t-1} dS_{t-1}) + \alpha_3(dP_{t-1}) + \alpha_4\left(\hat{P}_t^{BBO} - P_t\right) + \alpha_5 \% ExchBid_t + \alpha_6 \% ExchAsk_t + \varepsilon_{t+\tau},$$

where P_t is the option price (can be either call price or put price) at time t. $\hat{P}_t^{BSM}$ is the Black-Scholes model implied option price (the logic behind is that usually option price responding to stock price with lag). $\hat{P}_t^{BBO}$ represents the difference between the average quote midpoint and across all exchanges (BBO average). $\% ExchBid_t$ ($\% ExchAsk_t$) represents percentage of exchanges that report best NBBO bid (ask) price. In practice we use this model to predict option price 10min or 30min later ($\tau = 10 \min or\ 30min$).

In the paper by Muravyev and Pearson (2016), this model is relatively good at estimating the efficient trading costs by option market makers. Therefore, in this article, we use it to identify option market maker's trades from others with slight variations. The identification strategy goes as follows: For ***Buy*** trades, if $P_{t+\tau} > P_t$, then we categorize this trade as a good-buy ($or\ GB$) trade; otherwise we call it bad-buy ($or\ BB$). Similarly, for ***Sell*** trades, if $P_{t+\tau} < P_t$ then we call this trade good-sell ($or\ GS$) trade, otherwise categorizing as bad-sell ($or\ BS$). In other words, in order to limit their trading costs, option market makers should trade in the moving direction of the price. Combining with Call and Put category, together we categorize trade into six categories: good-buy-call ($or\ GBC$), good-sell-call ($or\ GSC$), bad-buy-call ($or\ BBC$) or bad-sell-call ($or\ BSC$), good-buy-put ($or\ GBP$), bad-buy-put ($or\ BBP$), good-sell-put ($or\ GSP$), and bad-sell-put ($or\ BSP$).

The trades that are categorized as ***Bad*** trades don't mean those trades are error trades, it just means those trades are not cost-efficient evaluated using our algorithms. However, we want to emphasize here that trades that called ***Bad*** trades are not necessarily all from retail investors and institutional investors, they also include trades from noisy traders (in other words, this is a semi-pooling equilibrium). Despite of this efficiency, the signals we construct from these ***Bad*** trade order imbalances are far-more precise than total order imbalances, which has proven to be noisy and uninformative. In particular, we only emphasize the definition of normalized BBC/C, BBP/P, and $BBPC$ here. The other order imbalances are not informative in predicting future stock returns and are not our focus in this paper. Normalized BBC/C, BBP/P, and $BBPC$ are defined as follows:

$$BBC/C = \frac{BBC}{TC + 5},$$

$$BBP/P = \frac{BBP}{TP + 5},$$

and,

$$BBPC = \frac{BBP}{BBP + BBC + 5},$$

where TC represents total call trading volume and is measured as $GBC + GSC + BBC + BSC$. TP represents total put trading volume and is measured as $GBP + GSP + BBP + BSP$. As expected, we argue that this measurement is quite private. Therefore, we expect the ISE disclosure may not have a very big impact on the long-term predictability of our private order imbalance measures. We will explore these issues in the rest of this section.

5.1. The Cross-Sectional Stock Return Predictability and ISE Disclosure Effect

First and foremost, we want to demonstrate that our execution-timing based order imbalance measures are efficient in predicting future cross-sectional stock returns, both in short and long horizon. We run Fama-MacBeth (1973) predictive regressions for our three constructed order imbalance measures, BBC/C, BBP/P, and $BBPC$, at 1-day, 1-week and 1-month horizon.

In Figure 3, we illustrate the time-series coefficients of BBC/C, BBP/P, and $BBPC$ in Panel A, Panel B and Panel C, respectively. As expected, either BBC/C, BBP/P or $BBPC$ shows strong 1-day announcement effect. For 1-week and 1-month horizon, besides, BBP/P or $BBPC$ shows robust and persistent predictability before and after ISE disclosure event. Unfortunately, for BBC/C, we do find significant forecasting ability before ISE disclosure. But after 2010, this predictability gradually weakened and died away.

To further validate our findings in Figure 3, we formally test the effect of ISE disclosure by introducing dummy variables and reported regression results in Table 3. The definitions of time dummies are stated in previous sections. The regression results of BBC/C, BBP/P or $BBPC$ are reported in Table 3 Panel A, Panel B and Panel C, respectively. In particular, Model 1 report overall predictability of our execution-timing order imbalance measures. Consistent with what we observe from the figure, all of our constructed order imbalance measures strongly and robustly predict future cross-sectional stock returns at 1-day horizon (announcement effect). However, unlike Pan and Poteshman (2006) and Pearson et al. (2016) documented open-buy measures, our execution-timing based BBP/P and $BBPC$ order imbalance measures consistently to show robust and significant predictability at 1-week and 1-month horizon. In particular, BBP/P predicts 1-week and 1-month with a t-value of -8.05 and -7.41 respectively. And $BBPC$ also predicts 1-week and 1-month horizon with a t-value of -4.31 and -3.93, respectively. Despite the satisfying performance $BBPC$ and BBP/P, the normalized BBC/C doesn't do a very good job at predicting long-term stock returns. In particular, predictability has weakened critically after 2010. From Model 3 in Table 3 Panel A, we can see that the coefficient is indifferent from zero for post-2010 period. However, as illustrated by Model 2 and Model 3 in Table 3 Panel B and Panel C, we also show that our long-term predictability still exists for BBP/P and $BBPC$.

Given the empirical results, we can reach at several conclusions: first of all, our execution-timing based order imbalance measures are effective at extracting informative option trades from option market makers' liquidity trades and noisy trades. Second, since our signals are privately constructed, the ISE disclosure doesn't have a crucial impact on the predictability of our order imbalance measures.

5.2. Predictability and Exchange Segmentation

Though we confirm that both short and long term predictability of our execution-timing order imbalance measures is robust and not affected by the ISE disclosure event, there is still another exception that our predictability may due to informed trades from other exchanges rather than ISE. To rule out this possibility, we re-construct our order imbalance measures separated by exchanges, e.g. ISE/CBOE/OTHER. As an illustration, order imbalances constructed from CBOE represents we only use option trades from CBOE and don't use information from other exchanges. Then, we run predictive regressions using order imbalance measures from different exchanges and draw the time-series of coefficients in Figure 4.

As illustrated by Figure 4 Panel A, Panel B and Panel C, it is obvious that the ISE disclosure event do not really affect the predictability of our privately-constructed order imbalance measures. Two conclusions can be reached: (1) our ISE-only execution-timing based on order imbalance measures robustly predict short and long term cross-sectional stock returns and are not crucially affected by ISE disclosure on November 2007, which is completely different from ISE open-buy order imbalances (e.g. Pan and Poteshman (2006), Pearson et al. (2016)). (2) We find no significant differences in predictability between ISE-only order imbalance measures and CBOE/OTHER-only order imbalance measures. This can be indirect evidence that even ISE started to sell their Open/Close profile to public investors, informed trades haven't fully fled away from trading on ISE.

5.3. Portfolio Performance

In this section, we explore the decile portfolio performance at 1-day/1-week/1-month horizon. Portfolios are sorted into decile by the end of each day based our execution-timing order imbalance measures (BBC/C , BBP/P and $BBPC$). Figure 5 displays decile portfolio performance as well as High-Low long-short strategy performance in bar graph. Exact numbers and t-statistics are reported in Table 4.

In Figure 5, we can see that the trend is most obvious for 1-day return, which is exactly consistent with the aforementioned evidence that the 1-day predictability is the strongest for every order imbalance measure we use. As forecasting horizon prolongs, the trend becomes less apparent, which is also consistent with a weaker predictability of these order imbalance measures in predicting long-term stock returns in the cross section.

As reported in Table 4 Panel A, the High-Low $BBPC$ (BBC/C , or BBP/P) strategy generates -8.39 (4.07, or -3.51) basis points FF3 alpha per day, equivalent to -23.5% (10.8%, or -9.25%) per annum. The statistical significance is also very impressive across all measures. To our satisfaction, though the predictability becomes weak at longer horizon, the High-Low long-short strategy still works well. The raw returns as well as FF3 alphas are statistically significant.

One interesting observation from Figure 5, the bottom decile portfolio bears unconvenational behaviors. One caveat here, the bottom decile, or ***Low***, portfolio contains and only contains stocks with order imbalance measures equaling to zero. Given our empirical evidence, those zero-order imbalance measures behave unusually, which reminds us of digging into details of those zero order imbalance stocks.

6. Conclusions

This article examines the informational content of option trading for future movements in underlying stock prices. In particular, we are trying to address two main questions here: (1) using an exogenous variation event, we try to quantify the impact of information disclosure on the predictability of future stock returns. (2) We also examine the characteristics of option informed trades: in particular, with implicit assumptions on transitory and persistent price impact, we use our self-developed execution-timing algorithms to separate option market makers' liquidity trades from investors' informed trades. We show that the cross-sectional predictability of underlying stock prices is mostly driven by valuable signals initiated by investors' who perceive superior information about future stock prices, while option market makers' liquidity order imbalances provide little guidance towards future stock price movements. We also show that the disclosure of private option trades information has a non-trivial impact on stock return predictability as well as the information absorption speed.

First of all, we show that option order imbalances can predict the cross-section of stock returns. We show that a large part of this predictability can be attributed as one-day stock return forecasting effect. Predictability of option order imbalances declines as forecasting horizon prolongs. In particular, we show that, the predictability of long-horizon predictability depends on the privacy of information. Public disclosure of option trades information has a crucial and negative impact on the predictability of option order imbalances.

To specifically examine what characteristics do those informed option trades have in common, we develop our testing algorithms based on few implicit but very critical assumptions: we argue that option market makers are primarily responsible for liquidity trades and informed investors who have superior information are responsible for informed trades that predicts future stock price movements. For liquidity trades, the most important factor is execution costs (option-trading is notoriously expensive), in other words we would like to call it "Temporary Impact". However, for informed trades that want to maximize information advantage and take advantage of option embedded leverage characteristics, trading cost is not of primary concern. Long-term "Persistent Impact" on stock price is much more important.

Furthermore, using identification algorithms, we can imprecisely distinguish between investor's trades and option market maker's trades and find that, the order imbalances from non-option market makers contain almost all information relevant for predicting future stock returns. In particular, we have shown that option order imbalance predictors constructed from our informed-trades pool can strongly predict cross-sectional stock returns at 1-day, as well as 1-week and 1-month horizon. The long-short portfolio (decile portfolios) can generate annual abnormal return ranging from 10% to 24% per annum. Our results are consistent with theories implying that option trading volume reflects the actions of informed traders, and the action of disclosing this information can facilitate asset price movements.

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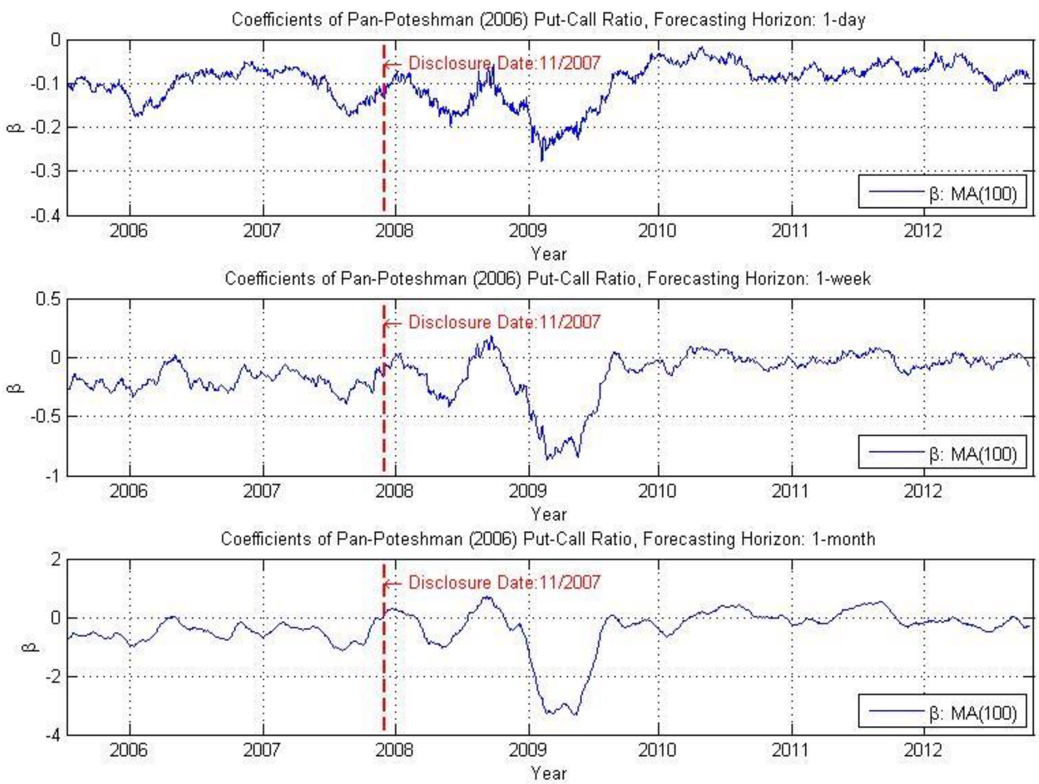
Figure 1. Predictability of Pan and Poteshman (2006) Put-Call Ratio

This figure examines the cross-sectional predictability of Pan and Poteshman (2006) put-call ratio measure using ISE dataset. Panel A plots the time series of estimated coefficients (100-day moving average) from Fama-MacBeth (1973) regression at daily frequency. Panel B plots average coefficients (red dot) and corresponding 95% confidence interval (blue error bar) by year. The predictability is tested at three horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day).

Panel A: Coefficients of Pan and Poteshman (2006) Put-Call Ratio: Daily Frequency



Panel B: Average Coefficients and 95% Confidence Interval of Pan and Poteshman (2006) Put-Call Ratio, by Year

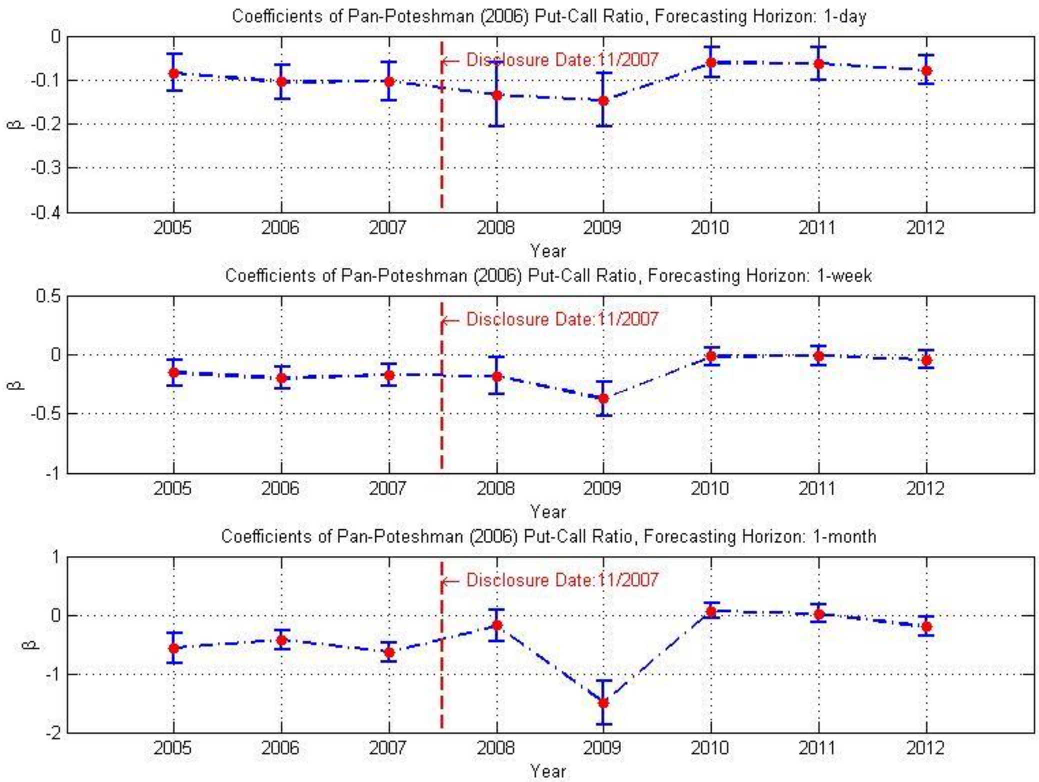
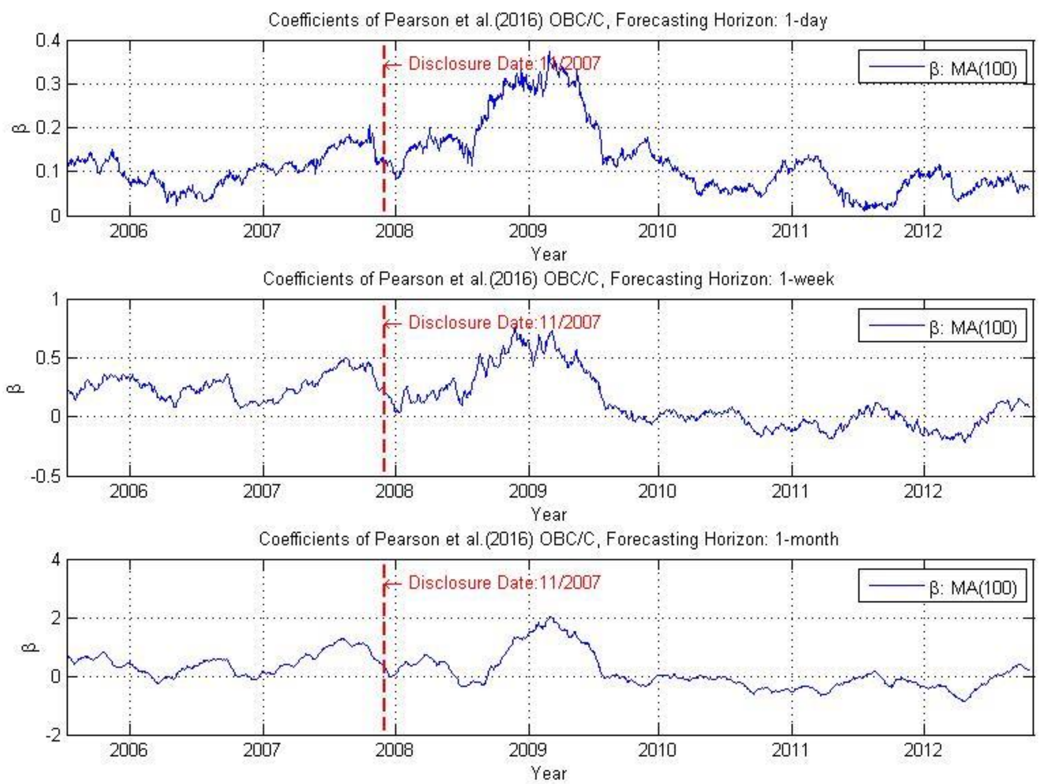


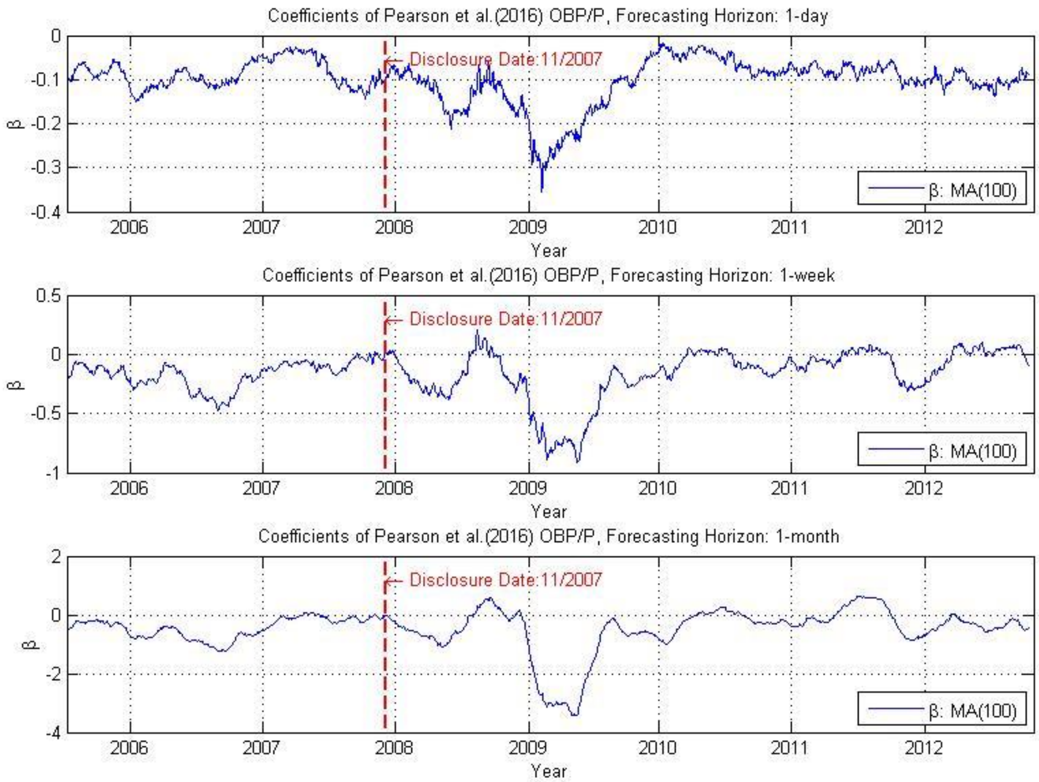
Figure 2. Predictability of Pearson et al. (2016) Order Imbalance Measures

This figure examines the cross-sectional predictability of Pearson et al. (2016) order imbalance measures using ISE dataset. Panel A.1 (Panel A.2) plots the time series of estimated coefficients (100-day moving average) of Pearson et al. (2016) OBC/C (OBP/P) measure from Fama-MacBeth (1973) regression at daily frequency. Panel B.1 (Panel B.2) plots average coefficients (red dot) and corresponding 95% confidence interval (blue error bar) by year. The predictability is tested at three horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day).

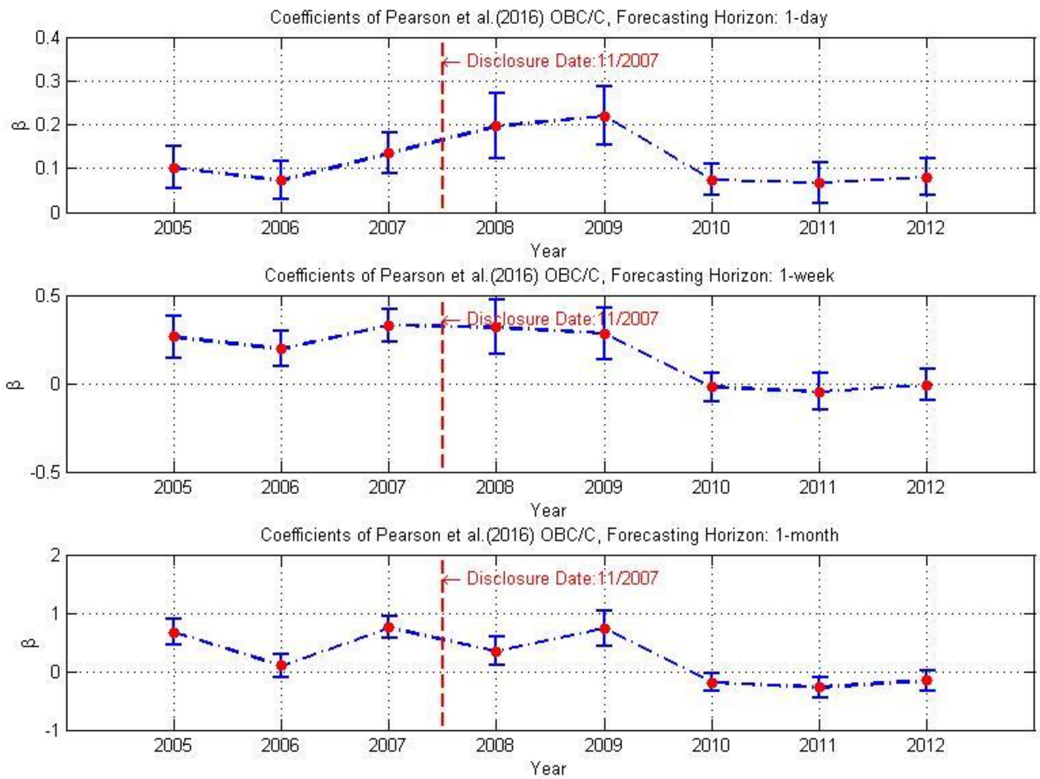
Panel A.1: Coefficients of Pearson et al. (2006) OBC/C measure: Daily Frequency



Panel A.2: Coefficients of Pearson et al. (2006) OBP/P measure: Daily Frequency



Panel B.1: Average Coefficients and 95% Confidence Interval of Pearson et al. (2006) OBC/C measure, by Year



Panel B.2: Average Coefficients and 95% Confidence Interval of Pearson et al. (2006) OBP/P measure, by Year

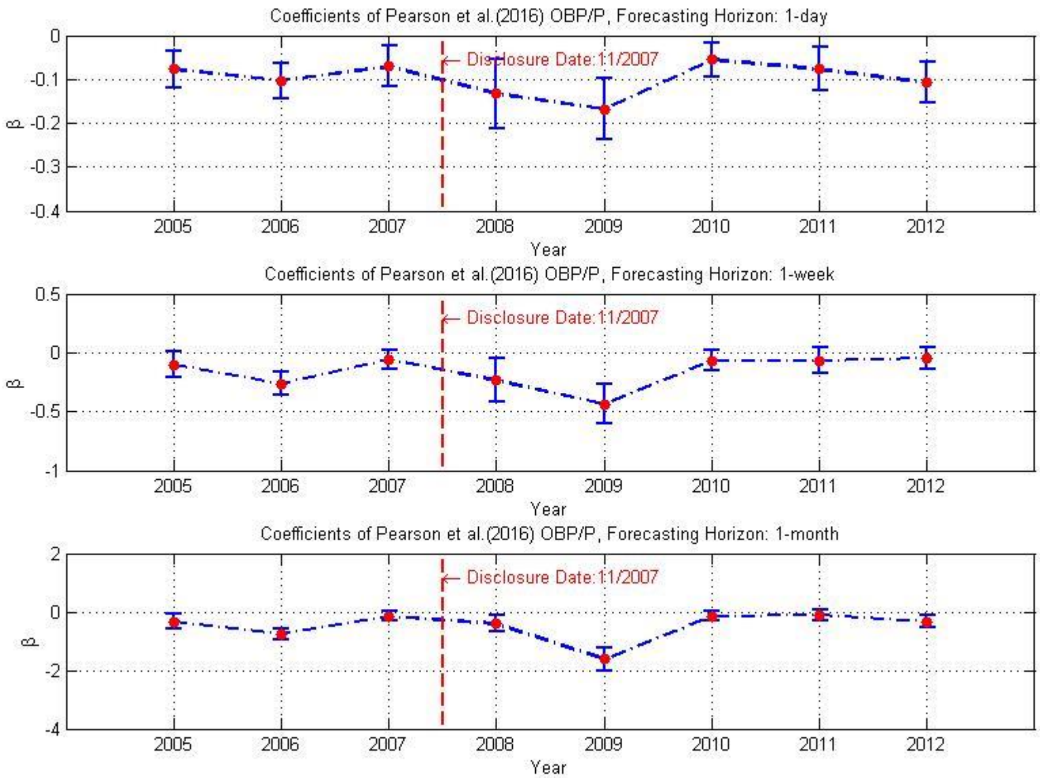
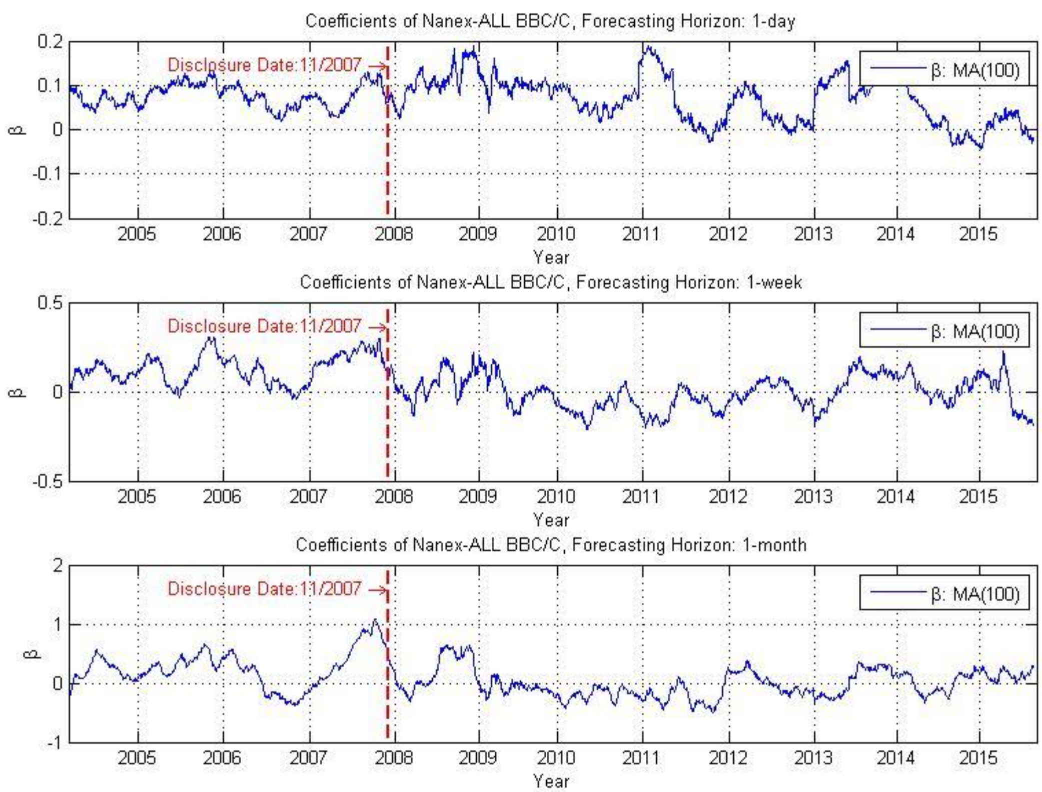


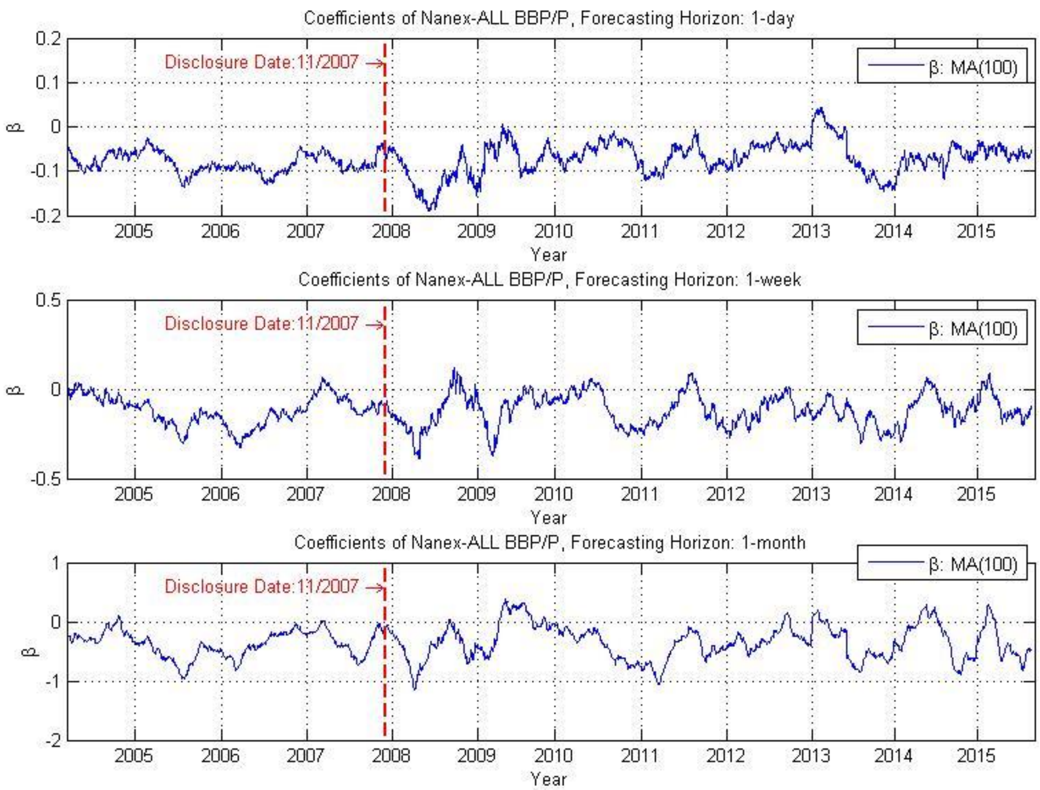
Figure 3. Predictability of Execution-Timing based Order Imbalance Measures

This figure examines the cross-sectional predictability of our execution-timing based order imbalance measures using Nanex dataset. Panel A plots the time series of estimated coefficients (100-day moving average) of normalized bad-buy call order imbalance measure (BBC/C). Panel B plots the time series of estimated coefficients (100-day moving average) of normalized bad-buy put order imbalance measure (BBP/P). Panel C plots the time series of estimated coefficients (100-day moving average) of normalized bad-buy put-call order imbalance measure (BBPC). The predictability is tested at three horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day).

Panel A: Coefficients of Normalized Bad-Buy Call Order Imbalance Measure (BBC/C): Daily Frequency



Panel B: Coefficients of Normalized Bad-Buy Put Order Imbalance Measure (BBP/P): Daily Frequency



Panel C: Coefficients of Normalized Bad-Buy Put-Call Order Imbalance Measure (BBPC): Daily Frequency

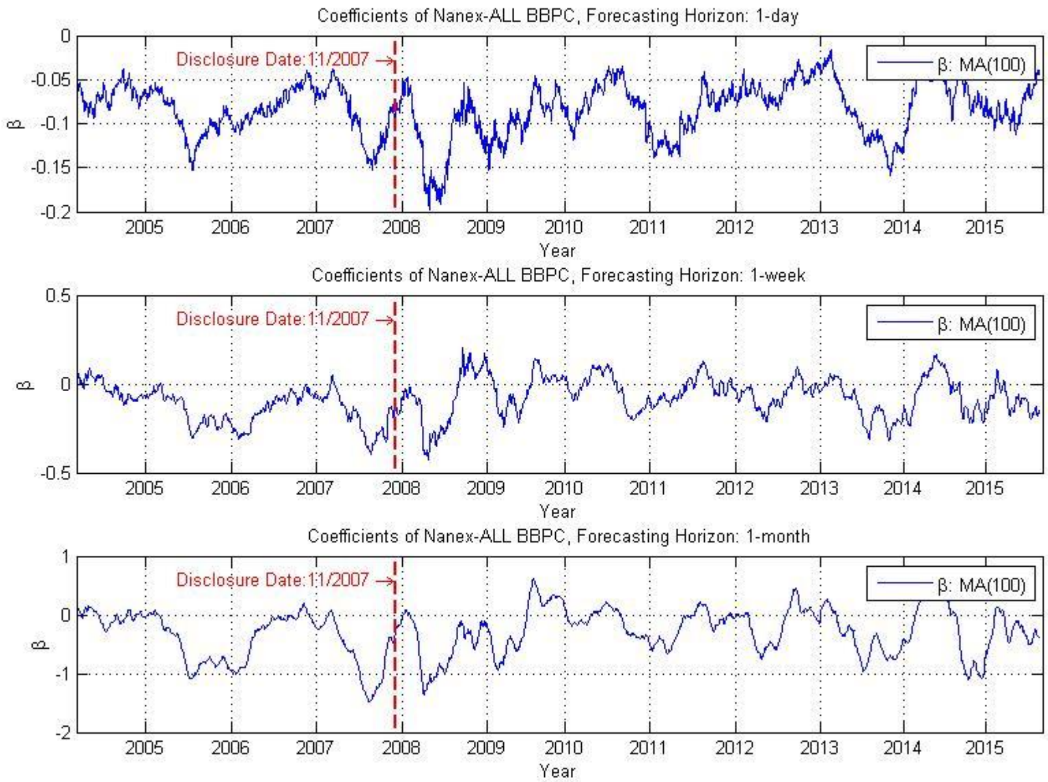
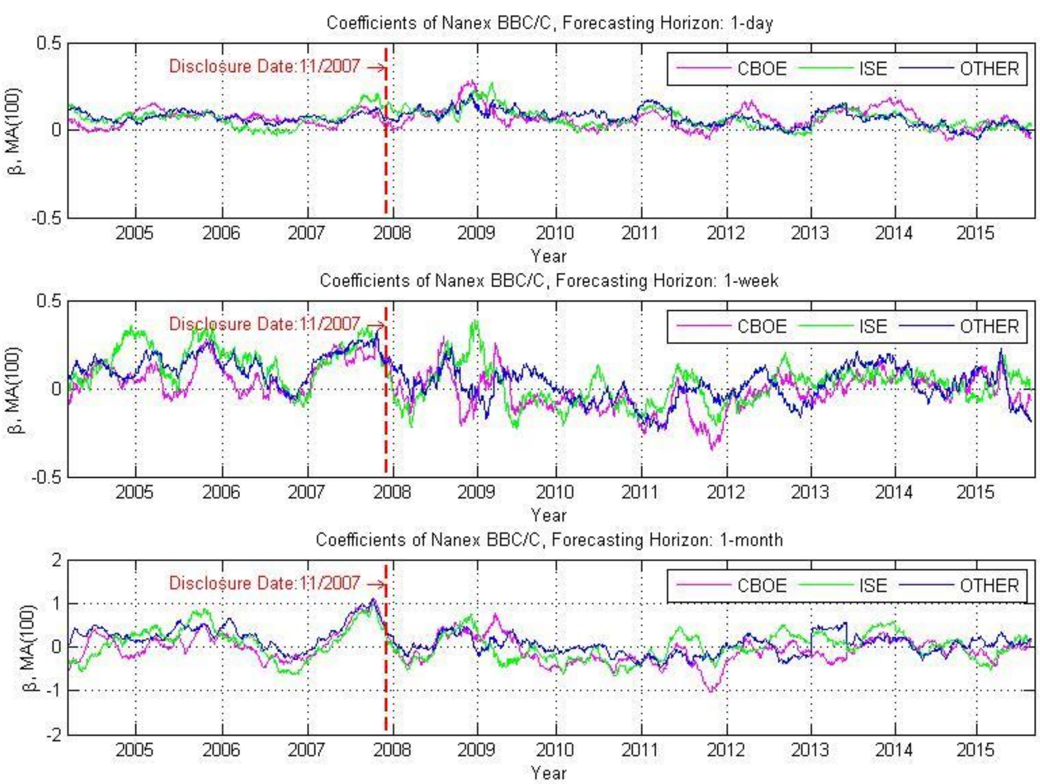


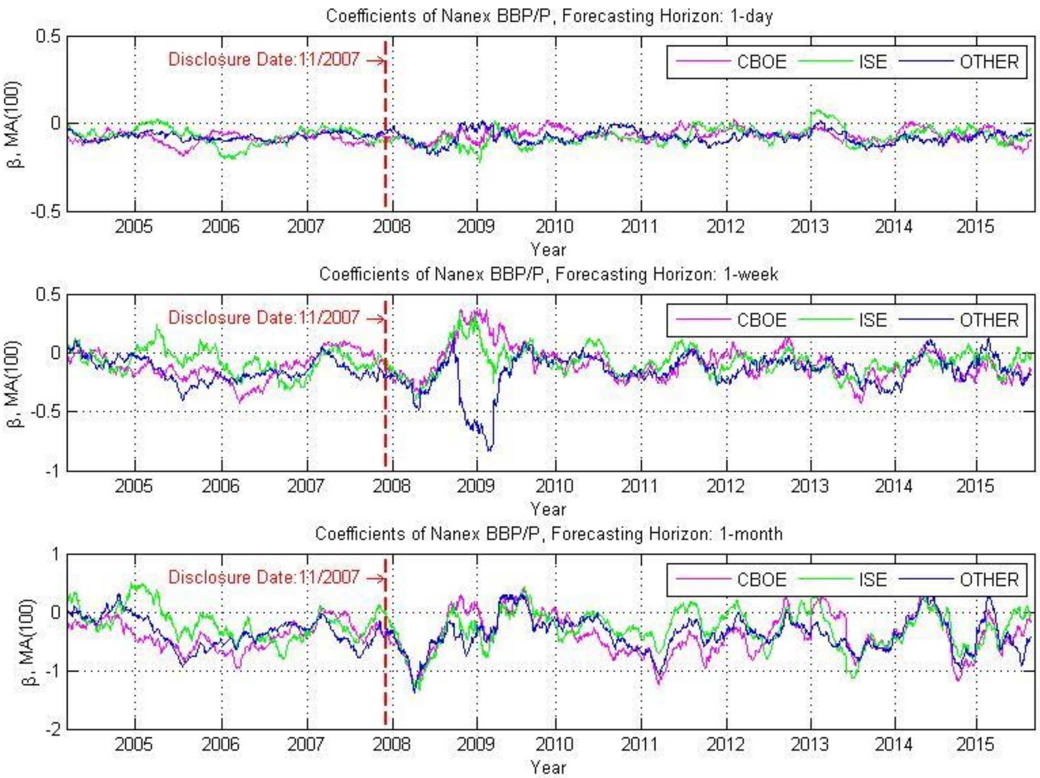
Figure 4. Predictability of Execution-Timing based Order Imbalance Measures, by Different Exchanges

This figure examines the cross-sectional predictability of our execution-timing based order imbalance measures using Nanex dataset but categorized according to different exchanges: CBOE, ISE and OTHER. Panel A plots the time series of estimated coefficients (100-day moving average) of normalized bad-buy call order imbalance measure (BBC/C). Panel B plots the time series of estimated coefficients (100-day moving average) of normalized bad-buy put order imbalance measure (BBP/P). Panel C plots the time series of estimated coefficients (100-day moving average) of normalized bad-buy put-call order imbalance measure (BBPC). The predictability is tested at three horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day).

Panel A: Coefficients of Normalized Bad-Buy Call Order Imbalance Measure (BBC/C) by Different Exchanges: Daily Frequency



Panel B: Coefficients of Normalized Bad-Buy Put Order Imbalance Measure (BBP/P) by Different Exchanges: Daily Frequency



Panel C: Coefficients of Normalized Bad-Buy Put-Call Order Imbalance Measure (BBPC) by Different Exchanges: Daily Frequency

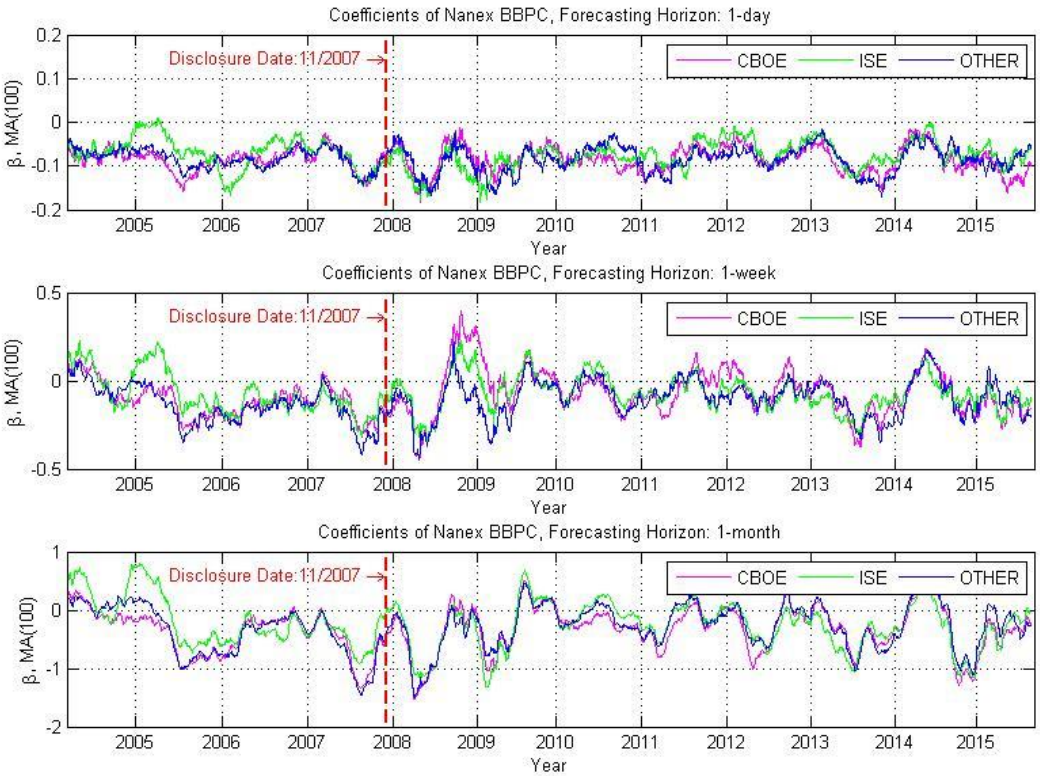
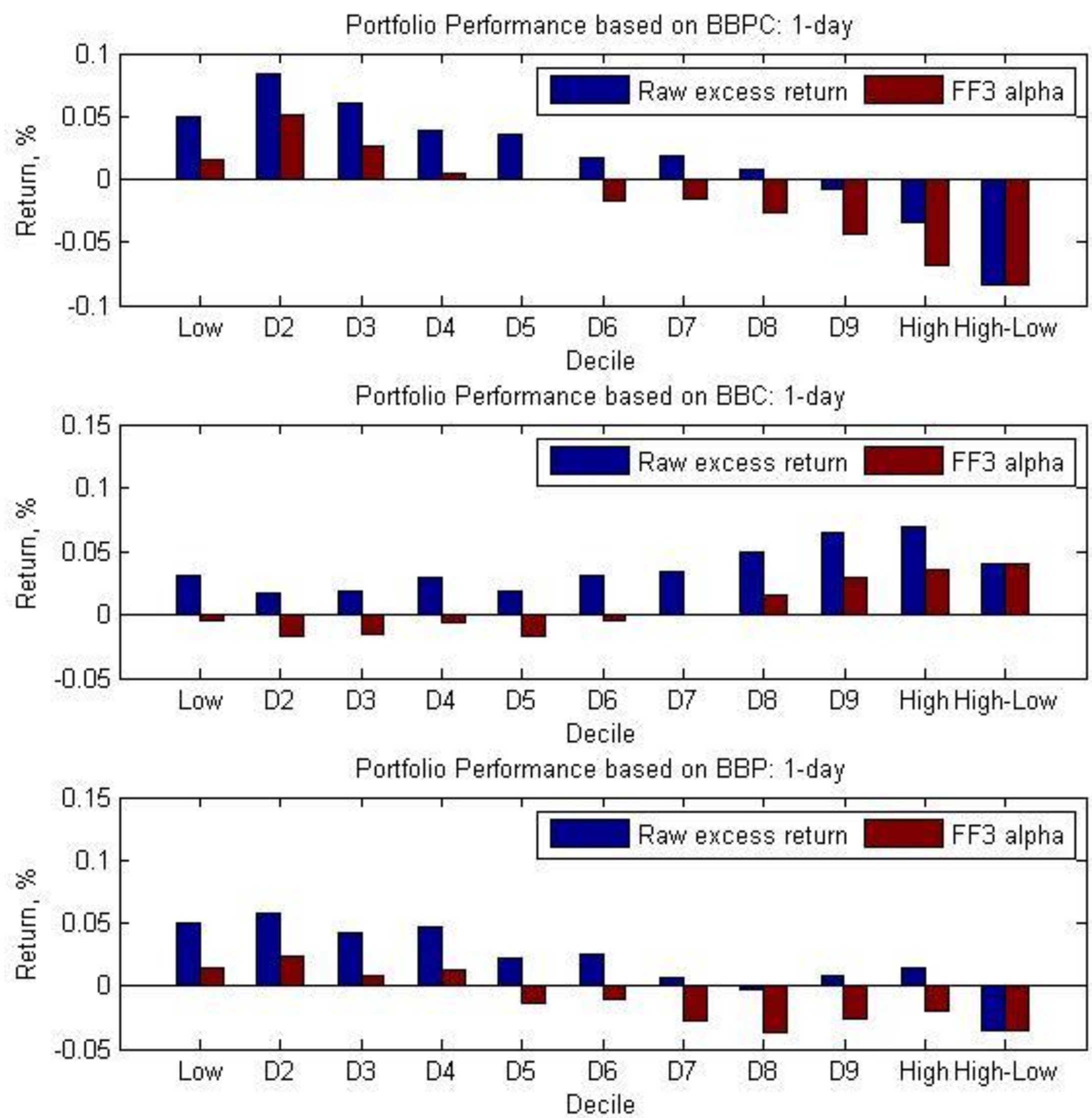


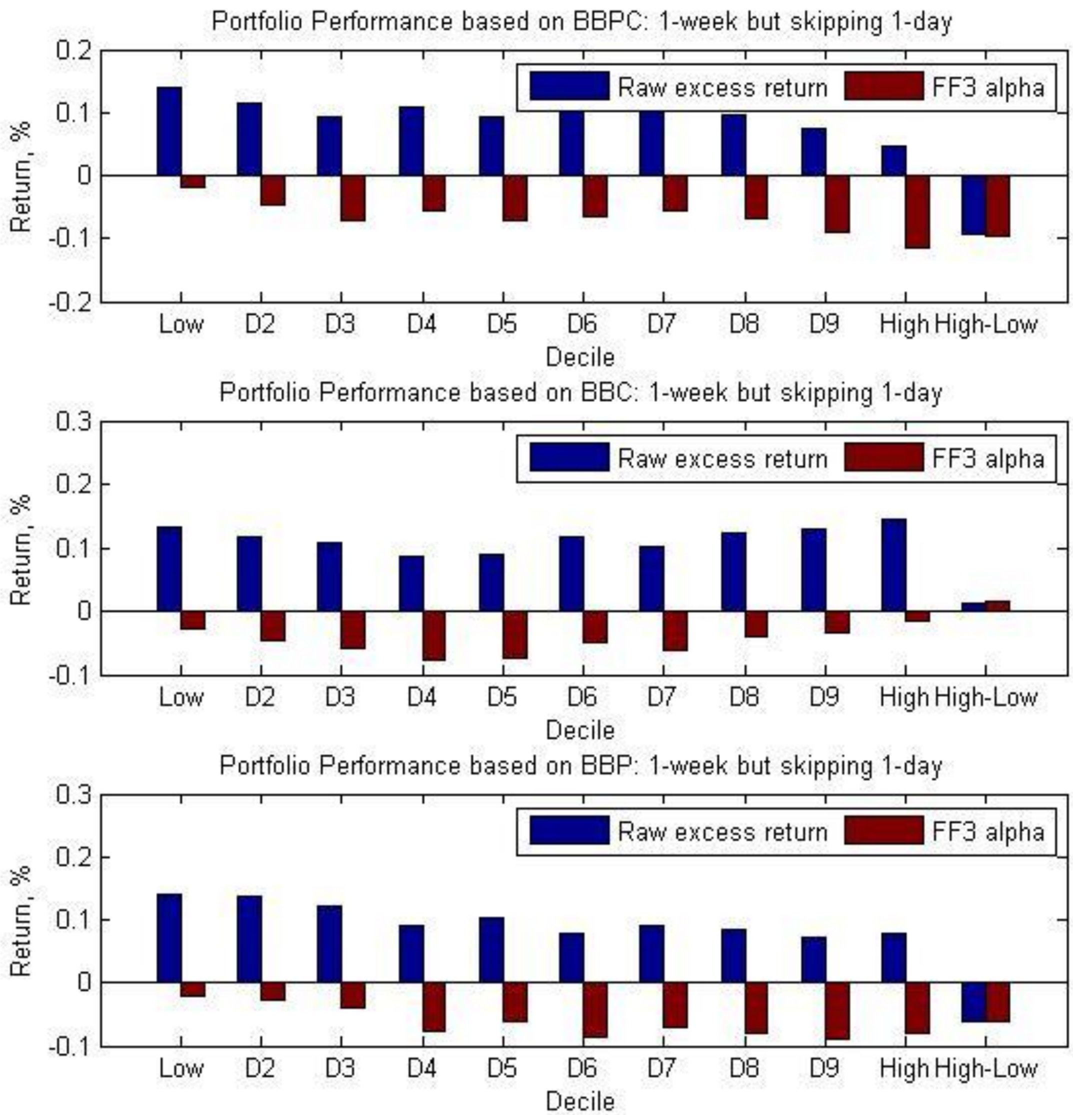
Figure 5. Portfolio-Sorting Results based on our Execution-Timing Order Imbalance Measures

This figure examines the portfolio performance based on our execution-timing order imbalance measures. By the end of each day, stocks are sorted into decile portfolios based on our order imbalance measures. Portfolio performance is then recorded at different holding horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day). Panel A displays decile portfolio performance at 1-day horizon. Panel B displays decile portfolio performance at 1-week (but skipping 1-day) horizon. Panel C displays decile portfolio performance at 1-month (but skipping 1-day) horizon. Both raw excess return and Fama-French 3 factor alpha are reported.

Panel A: Decile Portfolio Performance at 1-day Horizon



Panel B: Decile Portfolio Performance at 1-week (but skipping 1-day) Horizon



Panel C: Decile Portfolio Performance at 1-month (but skipping 1-day) Horizon

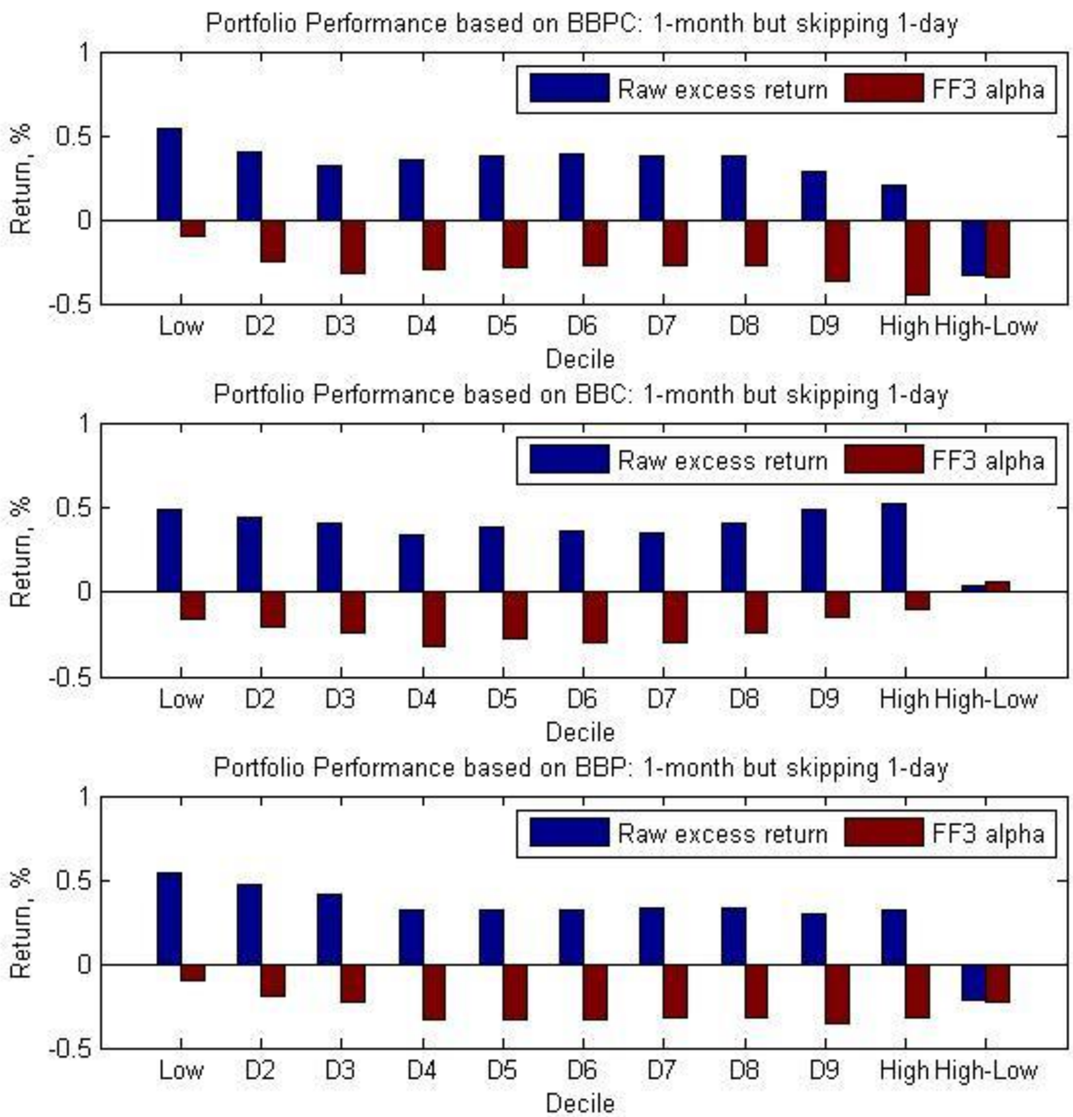


Table 1. The Disclosure Effect on the Predictability of Pan and Poteshman (2006) Order Imbalance Measures

This table examines the public disclosure effect on the predictability of Pan and Poteshman (2006) put-call ratio order imbalance measure. We test the disclosure effect by running time-series regressions on the coefficients from Fama-MacBeth (1973) 1st-stage results. Dummy variables are constructed as: D(date>=200712) equals 1 if date>=12/2007 and 0 otherwise. The definitions for D(date>=200712 & date<=200912) and D(date>=201001) are similar to D(date>=200712). We validate predictability at three different horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day). The sample spans from May 2005 to December 2012. T-stats are computed using Newey-West (1987) standard errors.

	Forecasting horizon: 1-day			Forecasting horizon: 1-week			Forecasting horizon: 1-month		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.0977	-0.0991	-0.0991	-0.1437	-0.1785	-0.1785	-0.4151	-0.539	-0.539
	(-8.247)	(-8.2309)	(-8.2309)	(-3.395)	(-7.4487)	(-7.4487)	(-2.558)	(-6.3713)	(-6.3713)
D(date>=200712)		0.0021			0.0528			0.1877	
		(0.1035)			(0.7828)			(0.7175)	
D(date>=200712 & date<=200912)			-0.0412			-0.0928			-0.2632
			(-1.7789)			(-0.9323)			(-0.5676)
D(date>=201001)			0.0319			0.1528			0.4976
			(2.3275)			(5.232)			(4.0627)
Adjust R-Squared, %	0	-0.05	0.48	0	0.03	1.27	0	0.19	2.96

Table 2. The Disclosure Effect on the Predictability of Pearson et al. (2016) Order Imbalance Measures

This table examines the public disclosure effect on the predictability of Pearson et al. (2016) open-buy order imbalance measures. We test the disclosure effect by running time-series regressions on the coefficients from Fama-MacBeth (1973) 1st-stage results. Dummy variables are constructed as: D(date>=200712) equals 1 if date>=12/2007 and 0 otherwise. The definitions for D(date>=200712 & date<=200912) and D(date>=201001) are similar to D(date>=200712). We validate predictability at three different horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day). Panel A reports results using open-buy call measure (OBC/C). Panel B reports results using open-buy put measure (OBP/P). The sample spans from May 2005 to December 2012. T-stats are computed using Newey-West (1987) standard errors.

Table 2 Panel A: Open-Buy Call measure: OBC/C

	Forecasting horizon: 1-day			**Forecasting horizon: 1-week**			**Forecasting horizon: 1-month**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	0.1193	0.1023	0.1023	0.1588	0.2594	0.2594	0.2241	0.4788	0.4788
	(5.7789)	(6.8738)	(6.8738)	(2.7841)	(7.2644)	(7.2644)	(1.5392)	(3.3916)	(3.3916)
D(date>=200712)		0.0258			-0.1524			-0.3859	
		(0.7789)			(-1.7666)			(-1.611)	
D(date>=200712 & date<=200912)			0.1055			0.0415			0.0507
			(2.7438)			(0.3743)			(0.1562)
D(date>=201001)			-0.0289			-0.2856			-0.6858
			(-1.7011)			(-6.214)			(-4.0979)
Adjust R-Squared, %	0	0.03	1.6	0	0.58	2.58	0	1.05	3.86

Table 2 Panel B: Open-Buy Put measure: OBP/P

	Forecasting horizon: 1-day			Forecasting horizon: 1-week			Forecasting horizon: 1-month		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.1001	-0.085	-0.085	-0.1619	-0.1481	-0.1481	-0.4857	-0.433	-0.433
	(-7.7115)	(-8.0801)	(-8.0801)	(-3.6414)	(-3.0795)	(-3.0795)	(-3.1013)	(-3.0626)	(-3.0626)
D(date>=200712)		-0.0229			-0.0209			-0.08	
		(-1.0807)			(-0.2537)			(-0.3006)	
D(date>=200712 & date<=200912)			-0.0644			-0.18			-0.5459
			(-2.3596)			(-1.7175)			(-1.332)
D(date>=201001)			0.0056			0.0885			0.2402
			(0.3799)			(1.6082)			(1.366)
Adjust R-Squared, %	0	0.01	0.37	0	-0.04	1.1	0	-0.01	2.55

Table 3. The Disclosure Effect on the Predictability of Execution-Timing based Order Imbalance Measures

This table examines the public disclosure effect on the predictability of our execution-timing order imbalance measures using Nanex dataset. We test the disclosure effect by running time-series regressions on the coefficients from Fama-MacBeth (1973) 1st-stage results. Dummy variables are constructed as: D(date>=200712) equals 1 if date>=12/2007 and 0 otherwise. The definitions for D(date>=200712 & date<=200912) and D(date>=201001) are similar to D(date>=200712). We validate predictability at three different horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day). Panel A reports results using Nanex bad-buy call measure (BBC/C). Panel B reports results using Nanex bad-buy put measure (BBP/P). Panel C reports results using Nanex bad-buy put-call measure (BBPC). The sample spans from January 2004 to December 2015. T-stats are computed using Newey-West (1987) standard errors.

Table 3 Panel A: Nanex Bad-Buy Call measure: BBC/C

	Forecasting horizon: 1-day			Forecasting horizon: 1-week			Forecasting horizon: 1-month		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	0.0713	0.08	0.08	0.0328	0.1189	0.1189	0.0669	0.2109	0.2109
	(7.5941)	(9.303)	(9.303)	(1.4775)	(5.1304)	(5.1304)	(1.1724)	(2.0026)	(2.0026)
D(date>=200712)		-0.0132			-0.1298			-0.217	
		(-0.8271)			(-4.1428)			(-1.8569)	
D(date>=200712 & date<=200912)			0.027			-0.083			-0.1316
			(1.8371)			(-2.188)			(-0.8807)
D(date>=201001)			-0.027			-0.1459			-0.2464
			(-1.5861)			(-4.2471)			(-2.0603)
Adjust R-Squared, %	0	-0.01	0.15	0	0.52	0.56	0	0.37	0.4

Table 3 Panel B: Nanex Bad-Buy Put measure: BBP/P

	Forecasting horizon: 1-day			Forecasting horizon: 1-week			Forecasting horizon: 1-month		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.0725	-0.0798	-0.0798	-0.1168	-0.1226	-0.1226	-0.3526	-0.3775	-0.3775
	(-11.3592)	(-12.6479)	(-12.6479)	(-8.0477)	(-4.3967)	(-4.3967)	(-7.4049)	(-5.2452)	(-5.2452)
D(date>=200712)		0.011			0.0087			0.0374	
		(1.0005)			(0.2691)			(0.3884)	
D(date>=200712 & date<=200912)			-0.0102			0.0015			0.1361
			(-0.4974)			(0.0355)			(0.8968)
D(date>=201001)			0.0183			0.0112			0.0035
			(1.7556)			(0.3365)			(0.0366)
Adjust R-Squared, %	0	-0.02	0.01	0	-0.03	-0.06	0	-0.02	0.01

Table 3 Panel C: Nanex Bad-Buy Put-Call measure: BBPC

	Forecasting horizon: 1-day			Forecasting horizon: 1-week			Forecasting horizon: 1-month		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	-0.0827	-0.0828	-0.0828	-0.0837	-0.1239	-0.1239	-0.2885	-0.382	-0.382
	(-14.6531)	(-10.532)	(-10.532)	(-4.3029)	(-3.5887)	(-3.5887)	(-3.928)	(-2.4272)	(-2.4272)
D(date>=200712)		0.0002			0.0606			0.1409	
		(0.0215)			(1.5223)			(0.7864)	
D(date>=200712 & date<=200912)			-0.0233			0.0623			0.0747
			(-1.627)			(1.0346)			(0.2938)
D(date>=201001)			0.0083			0.0601			0.1637
			(0.7631)			(1.4841)			(0.9336)
Adjust R-Squared, %	0	-0.03	0.05	0	0.11	0.08	0	0.16	0.17

Table 4. Portfolio Performance sorted on our Execution-Timing Order Imbalance Measures

This table displays portfolio performances based on our execution-timing order imbalance measures. By the end of each day, stocks are sorted into decile portfolios based on our order imbalance measures. Portfolio performance is then recorded at different holding horizons: 1-day ahead, 1-week ahead (but skipping 1-day), 1-month ahead (but skipping 1-day). Panel A displays decile portfolio performance at 1-day horizon. Panel B displays decile portfolio performance at 1-week (but skipping 1-day) horizon. Panel C displays decile portfolio performance at 1-month (but skipping 1-day) horizon. Both raw excess return and Fama-French 3 factor alpha (FF3 alpha) are reported. The sample spans from January 2004 to December 2015. T-stats are computed using Newey-West (1987) standard errors.

Table 4 Panel A: Forecasting Horizon: 1-day

	Portfolio Performance										
BBC/C											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.0301	0.0176	0.0192	0.0293	0.0184	0.03	0.0346	0.0494	0.0639	0.0697	0.0395
	(1.3384)	(0.7415)	(0.8404)	(1.3368)	(0.8707)	(1.4346)	(1.4546)	(2.1599)	(2.9233)	(2.9496)	(5.9849)
FF3 alpha, %	-0.0051	-0.0176	-0.0159	-0.0058	-0.0165	-0.0044	0.0002	0.015	0.0298	0.0358	0.0407
	(-0.9515)	(-2.9159)	(-2.5899)	(-0.6976)	(-2.9199)	(-0.6247)	(0.0216)	(1.5556)	(4.2443)	(4.3355)	(6.1268)
BBP/P											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.0498	0.0576	0.043	0.0469	0.022	0.0246	0.0066	-0.0023	0.0088	0.0145	-0.0351
	(2.307)	(2.4392)	(1.8674)	(2.1251)	(0.991)	(1.0476)	(0.2882)	(-0.0996)	(0.3683)	(0.6502)	(-7.4029)
FF3 alpha, %	0.015	0.0232	0.0086	0.0122	-0.0129	-0.0102	-0.028	-0.0373	-0.0257	-0.02	-0.0349
	(2.7425)	(3.2524)	(1.316)	(1.5749)	(-2.9391)	(-1.3297)	(-3.3549)	(-5.7747)	(-3.996)	(-2.7909)	(-7.3309)
BBPC											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.0498	0.0839	0.0607	0.0388	0.0351	0.017	0.0192	0.008	-0.0084	-0.0341	-0.0838

	(2.307)	(3.7253)	(2.85)	(1.7104)	(1.5361)	(0.6992)	(0.8269)	(0.3536)	(-0.3413)	(-1.4946)	(-11.7519)
FF3 alpha, %	0.015	0.0506	0.0267	0.0042	0.0001	-0.0177	-0.0158	-0.027	-0.0436	-0.0689	-0.0839
	(2.7425)	(5.9114)	(4.3012)	(0.5536)	(0.0187)	(-2.8294)	(-2.2066)	(-4.638)	(-6.5122)	(-9.6158)	(-12.4095)

Table 4 Panel B: Forecasting Horizon: 1-week but skipping 1-day

					Portfolio Performance						
BBC/C											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.1313	0.1157	0.1066	0.087	0.0907	0.1162	0.1018	0.1237	0.1282	0.1438	0.0128
	(1.0657)	(0.9338)	(0.8835)	(0.717)	(0.7485)	(0.9978)	(0.8279)	(1.0307)	(1.0841)	(1.1676)	(0.8341)
FF3 alpha, %	-0.0285	-0.0476	-0.0583	-0.0766	-0.0744	-0.0482	-0.0624	-0.0395	-0.0327	-0.015	0.0141
	(-1.553)	(-2.0133)	(-2.5471)	(-3.4109)	(-3.1748)	(-1.8772)	(-2.2408)	(-1.3469)	(-1.3838)	(-0.6174)	(0.9029)
BBP/P											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.1405	0.1361	0.123	0.0892	0.1031	0.0789	0.0911	0.0831	0.0725	0.0786	-0.0621
	(1.1467)	(1.117)	(1.0223)	(0.7341)	(0.8824)	(0.6554)	(0.7421)	(0.6968)	(0.5778)	(0.6468)	(-5.235)
FF3 alpha, %	-0.0194	-0.0277	-0.0409	-0.0771	-0.0624	-0.0863	-0.0719	-0.0812	-0.0905	-0.0808	-0.0614
	(-1.0193)	(-1.1415)	(-1.8551)	(-3.482)	(-2.4667)	(-3.7622)	(-2.6376)	(-2.755)	(-4.3693)	(-3.8488)	(-4.9033)
BBPC											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.1405	0.1144	0.0922	0.1071	0.0939	0.1014	0.1088	0.0956	0.0739	0.0473	-0.0934
	(1.1467)	(0.9403)	(0.7774)	(0.88)	(0.7849)	(0.8312)	(0.9234)	(0.8071)	(0.5932)	(0.3635)	(-3.9434)
FF3 alpha, %	-0.0194	-0.0473	-0.0712	-0.0571	-0.0713	-0.0642	-0.0554	-0.0668	-0.0902	-0.1153	-0.0958
	(-1.0193)	(-1.6745)	(-2.5534)	(-2.3566)	(-3.3247)	(-2.6739)	(-2.1661)	(-2.6244)	(-3.9267)	(-4.171)	(-3.9931)

Table 4 Panel C: Forecasting Horizon: 1-month but skipping 1-day

	Portfolio Performance										
BBC/C											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.4854	0.4438	0.407	0.334	0.3809	0.3552	0.3473	0.4065	0.4872	0.52	0.0396
	(0.9394)	(0.8752)	(0.8143)	(0.6705)	(0.7612)	(0.7162)	(0.6943)	(0.8151)	(0.9861)	(1.0387)	(1.016)
FF3 alpha, %	-0.1584	-0.2022	-0.2453	-0.3194	-0.2701	-0.2937	-0.3025	-0.2408	-0.1531	-0.107	0.0546
	(-1.8099)	(-2.3684)	(-2.8391)	(-3.5204)	(-2.7595)	(-2.864)	(-2.9695)	(-2.3767)	(-1.5832)	(-1.1699)	(1.5269)
BBP/P											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.5407	0.4686	0.4149	0.3252	0.3243	0.3219	0.3284	0.3301	0.2984	0.3204	-0.2187
	(1.0779)	(0.9278)	(0.8443)	(0.6425)	(0.6504)	(0.6366)	(0.6531)	(0.6496)	(0.5882)	(0.6265)	(-6.0867)
FF3 alpha, %	-0.0987	-0.1866	-0.2279	-0.3327	-0.3342	-0.3337	-0.321	-0.3213	-0.3504	-0.3229	-0.2242
	(-1.1369)	(-1.8524)	(-2.6172)	(-3.5484)	(-3.4014)	(-3.6307)	(-3.232)	(-3.4387)	(-3.8572)	(-3.3386)	(-6.2798)
BBPC											
	Low	D2	D3	D4	D5	D6	D7	D8	D9	High	High-Low
Raw return, %	0.5407	0.3966	0.321	0.3519	0.374	0.3893	0.3781	0.3736	0.2837	0.2053	-0.3339
	(1.0779)	(0.7946)	(0.6567)	(0.7071)	(0.7519)	(0.7775)	(0.7567)	(0.7292)	(0.5453)	(0.3818)	(-4.0161)
FF3 alpha, %	-0.0987	-0.2474	-0.3196	-0.2982	-0.2805	-0.2685	-0.2775	-0.2788	-0.3706	-0.4454	-0.3467
	(-1.1369)	(-2.2388)	(-2.9722)	(-2.8418)	(-2.8788)	(-2.9432)	(-3.0941)	(-3.0703)	(-3.6954)	(-4.1273)	(-4.5558)