0DTE Asset Pricing*

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Abstract

We document asset pricing implications of zero days-to-expiration (0DTE) options, which now comprise half of total S&P 500 option volume, and contrast them to longer-maturity contracts. A distinctive feature of the 0DTE market is that investors mainly require compensation for positive market returns, rather than negative returns. This is reflected in a high variance risk premium, which is largely driven by compensation for upside risk and negatively predicts market returns. Moreover, most 0DTEs appear mispriced from the perspective of risk-averse investors. Such mispricing is highly profitable before 2022, but dissipates after the daily availability of 0DTEs, consistent with growing integration with the underlying market.

Keywords: zero days-to-expiration (0DTE) options, equity premium, variance risk premium, pricing kernel, option returns.

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1 Introduction

We investigate the asset pricing implications of a new, relatively unexplored market: zero days-to-expiration (0DTE) S&P 500 options, i.e., options on the market index expiring by the end of the same day. These are weekly options that were listed at least a week before. Since May 2022, weeklies are listed every trading day by the Chicago Board Options Exchange (CBOE), resulting in the daily availability of 0DTE options. While one-month options were among the most traded contracts up to ten years ago, which partially justified the focus on these options by the literature, the landscape of the option market has changed dramatically more recently. Today, the daily volume of 0DTEs accounts for around half of total S&P 500 option volume, being thus by far the most traded maturity. The tremendous growth of these ultra short-maturity options has made them a trending topic in financial media outlets, trader forums and social media.

Our interest in 0DTE options is justified not only by the fact that they are now the most traded options in the market, but also because they contain new, valuable information about investors' risk preferences and risk premia over intra-daily horizons. Our goal is to extract this information by exploring, from different perspectives, how 0DTE option prices relate to the time series of high-frequency market returns. Our analysis provides new asset pricing stylized facts for ultra short-horizons and highlights how they are remarkably different from the empirical evidence of longer horizons.

We focus on two main questions. First, what is the compensation required by investors for bearing market risks over the day? The answer to this question is directly related to the intra-day pricing kernel implied by 0DTEs and its shape as a function of market returns.[1] We document a number of patterns in the equity and variance risk premia that are aligned with a nonmonotonic pricing kernel that is higher for positive returns than negative

[1]Starting with Jackwerth (2000), Aït-Sahalia and Lo (2000) and Rosenberg and Engle (2002), a large literature estimates this pricing kernel for longer horizons and documents a nonmonotonic shape, which is puzzling under a representative investor framework. See Cuesdeanu and Jackwerth (2018) for a survey.

returns, revealing that investors mainly require compensation for upside risk during the day. Second, are 0DTE option prices consistent with risk-averse investors? We find that violations of stochastic dominance increase as maturity shortens, with most 0DTEs appearing "mispriced".[2] A trading strategy exploiting this mispricing is highly profitable before 2022, but dissipates after the daily availability of 0DTEs. This is consistent with growing market efficiency and stronger integration of the underlying and option markets.

We start by analyzing average returns of 0DTE call and put options across strikes. These are informative about investors' preferences over intra-day market return states, i.e., about the shape of the pricing kernel projected onto market returns over the options horizon. Calls experience low returns overall, which decrease with the strike and eventually get highly negative. Following the rationale of Bakshi, Madan, and Panayotov (2010), this is evidence that the pricing kernel is increasing for some region of positive market returns, violating monotonicity. Put returns are also negative, especially out-of-the-money (OTM), indicating that the pricing kernel is a decreasing but steep function of market returns in the negative return region, consistent with aversion to downside risk.

Such risk preferences have strong implications for the equity premium over intra-daily horizons. Applying the decomposition of Beason and Schreindorfer (2022) to 0DTE options and realized market returns, we find that most of the intra-day equity premium stems from compensation to market returns between -5% and 0%. In contrast, positive return states have a negative contribution. This happens when the pricing kernel is nonmonotonic and marginal utility is high for positive market returns. In this case, investors would be willing to pay a premium to hold Arrow-Debreu securities paying in those states, i.e., they are willing to give up part of the compensation for equity risk.

Implications are also substantial for the variance risk premium. We first document

[2] We emphasize that "mispriced" here means only that we cannot reconcile 0DTE prices with information from the underlying market under risk-averse preferences. This does not mean that 0DTEs violate no-arbitrage conditions (which imply much wider bounds that 0DTEs in general satisfy) or that it is not possible to price 0DTEs with an option pricing model (see, e.g., Bandi, Fusari, and Renò, 2023).

that the average returns of at-the-money (ATM) delta-hedged calls and straddles are significantly negative. Since these strategies represent long positions in volatility, this means that investors are willing to pay a high premium to be protected against variance risk over the day (Bakshi and Kapadia, 2003; Coval and Shumway, 2001). This is confirmed when we compute a direct estimate of the variance risk premium, similarly to Bollerslev, Tauchen, and Zhou (2009). The (annualized) average variance risk premium implied by 0DTEs can be up to four times larger than what is observed for longer horizons.

To disentangle the compensation demanded by investors to bear variation risk in positive versus negative market returns, we respectively compute the "good" and "bad" components of the total variance risk premium, as in Kilic and Shaliastovich (2019). Strikingly, while at the one-month horizon the "good" variance risk premium is negative and the "bad" is highly positive, the upside risk premium increases as the option maturity shortens, until it becomes larger than the premium for downside risk over intra-daily horizons. This, again, would be consistent with a pricing kernel that is exceptionally high for positive market returns, such that investors demand compensation for these states of high marginal utility.

We further investigate whether 0DTE options contain predictive information for excess market returns over the day. We consider predictive regressions using the variance risk premium, risk-neutral moments (Bakshi, Kapadia, and Madan, 2003) and the equity premium lower bound of Martin (2017). From these variables, only the variance risk premium significantly predicts returns, but with a negative coefficient, which is at odds with the existing evidence for longer horizons (Bollerslev et al., 2009). By substituting the total variance risk premium with its "good" and "bad" components, we find that only the "good" component helps predict market returns, with a strong and statistically significant negative sign. In other words, the compensation for upside risk drives the result for the total variance risk premium. This negative relation is, once more, aligned with high marginal utility in states of positive market returns: the higher the pricing kernel in this region, the higher is the compensation for positive return variation risk and the more negative is the contribution of positive return states to the equity premium.

The findings above provide indirect evidence that the intra-day pricing kernel as a function of market returns is nonmonotonic and, in particular, high for positive returns. To confirm this evidence, we directly estimate the pricing kernel implied by 0DTE options and high-frequency market returns. For comparison, we also estimate pricing kernels for maturities up to one month. Over our sample, the average pricing kernel is mostly decreasing across returns when considering tenors between two weeks and one month, while as maturity shortens, a U-shaped pattern starts to appear. The pattern is more pronounced for 0DTEs, where the pricing kernel is actually higher for positive market returns than negative returns. This reveals that, over recent years, the nonmonotonicity of the pricing kernel has shifted to shorter maturities.

Our evidence shows that 0DTE option prices can only be jointly reconciled with the physical distribution of market returns under a pricing kernel displaying pronounced nonmonotonicity. However, if we entertain the possibility that the 0DTE option market is segmented, there could still be a different risk-averse trader in the market index that is marginal in each option. To test for that, we compute, for each option, price bounds from the physical distribution consistent with all pricing kernels that are monotonically decreasing in market returns (Ritchken, 1985). Over our sample, only around 30% of 0DTE options (and 6% of the ATM options) satisfy these bounds, which is again in stark contrast with evidence from longer horizons (Almeida and Freire, 2022). In fact, we show that around 97% of one-month options satisfy stochastic dominance bounds, while violations increase monotonically as maturity shortens.

As a result, 0DTE options are mostly "mispriced", in the sense that they do not reflect the risks implied by the time series of intra-day market returns under risk-averse preferences. To assess the economic significance of this mispricing, we consider a trading strategy purchasing (writing) the delta-hedged ATM option if it is cheap (expensive) according to risk-averse investors, i.e., if its price represents a lower (upper) bound violation. Up to 2022, this strategy is highly profitable, even after transaction costs, with a Sharpe ratio about ten times as large as that obtained by always writing the delta-hedged ATM option, that is, exploiting the variance risk premium. However, after the daily availability of 0DTEs and the associated increase in liquidity and attention to these options, the profitability dissipates. This indicates that the 0DTE market has become more efficient and closely integrated with the underlying market over the recent years.

The remainder of the paper is organized as follows. After a brief discussion of the related literature, Section 2 describes the theoretical framework behind our analysis. Section 3 presents the data and implementation details of the methods we use. Section 4 contains our empirical analysis. Section 5 reports robustness results with respect to different subsamples and monetary policy announcements. Section 6 concludes the paper. Appendix A collects the figures and tables of the paper.

1.1 Related literature

Our paper mainly relates to three strands of the literature. The first strand consists of an increasing number of papers studying the new 0DTE option market from different lenses. Brogaard, Han, and Won (2023) show that a higher fraction of 0DTE option trading increases the volatility of the underlying asset, while Dim, Eraker, and Vilkov (2024) and Adams, Fontaine, and Ornthanalai (2024) provide contrary evidence based on net open interest measures. Beckmeyer, Branger, and Gayda (2023) document that 0DTE options are popular among retail traders, even though these investors mainly experience losses in this market.[3] Bandi et al. (2023) present a novel option pricing formula designed

[3]While 0DTE options account for more than 75% of retail trading in S&P 500 options, the vast majority of 0DTE S&P 500 trading (around 94%) is still attributable to institutional investors.

for 0DTEs and investigate how leverage and volatility-of-volatility affect instantaneous risk premia. Vilkov (2023) explores the performance of 0DTE option trading strategies. Focusing on 1DTE options instead, Johannes, Kaeck, Seeger, and Shah (2024) analyze option returns around macroeconomic announcements. Chong and Todorov (2024) use 0DTEs to show that there is no segmentation between the equity and option markets based on restrictions for how short-horizon volatility should behave.[4] We contribute by recovering investors' risk preferences implied by 0DTEs, analyzing their implications for intra-day equity and variance risk premia, examining whether these options are mispriced relative to the underlying asset in the stochastic dominance sense, and comparing these findings to those from longer-maturity options.

The second strand recovers information about investors' expectations and risk preferences from relatively long-maturity options. Jackwerth (2000), Aït-Sahalia and Lo (2000) and Rosenberg and Engle (2002) estimate the projection of the pricing kernel onto market return states. Almeida and Freire (2022) find that S&P 500 option prices satisfy bounds consistent with risk-averse investors, where the preferences of the marginal agent vary across the options. Beason and Schreindorfer (2022) decompose the equity premium into different parts of the return state space. Bollerslev et al. (2009) show that the variance risk premium is generally positive and helps predict market returns. Bollerslev, Todorov, and Xu (2015) and Andersen, Fusari, and Todorov (2015, 2017) document the special role of compensation for jump risk in determining market risk premia. Using information from the new 0DTE market, which is the most relevant option market today, we provide novel asset pricing stylized facts for intra-daily horizons that are strikingly different from those obtained for longer horizons. In particular, we study the intra-day pricing kernel implied by 0DTEs.[5] As a methodological contribution, we discuss how all these elements

[4]As an implication of their result, the aggregate pricing kernel that reconciles 0DTE option prices with high-frequency market returns exists, which is the object of our study.

[5]Relatedly, Aleti and Bollerslev (2024) study intra-day realizations of a pricing kernel obtained from high-frequency returns of factors constructed from a monthly conditioning set of variables. In contrast,

are connected through the shape of the pricing kernel as a function of market returns.

The third literature strand investigates return predictability over relatively short horizons. Gao, Han, Zhengzi Li, and Zhou (2018) and Baltussen, Da, Lammers, and Martens (2021) document intra-day momentum patterns across different markets, relating them to infrequent portfolio rebalancing and hedging demand, respectively. Aït-Sahalia, Fan, Xue, and Zhou (2022) study the predictability of ultra high-frequency stock returns using machine learning methods. Aleti, Bollerslev, and Siggaard (2023) predict intra-day market returns with high-frequency cross-sectional returns of the factor zoo. Almeida, Ardison, Freire, Garcia, and Orlowski (2023), Almeida, Freire, Garcia, and Hizmeri (2023) and Alexiou, Bevilacqua, and Hizmeri (2023) use high-frequency market returns, cross-sectional stock returns and option returns, respectively, to estimate volatility and tail risk measures and predict risk premia over daily horizons. We show that 0DTEs contain useful predictive information about intra-day risk premia over the options horizon. More specifically, the variance risk premium negatively predicts excess market returns over the day, which is driven by a strong negative relation between the premium for positive return variation risk and future market returns.

2 Theoretical background

In this section, we present the theoretical background behind our analysis of the asset pricing implications of 0DTE options. We first describe what is the pricing kernel implied by options. Then, we discuss its relation with expected option returns, market risk premia and option price bounds. Finally, we explain how this framework will be used to study the 0DTE option market.

the pricing kernel we analyze is a function of market returns that is forward-looking and conditional on the investors' information set at the time of the day that the 0DTE options are observed.

2.1 The pricing kernel

In the absence of arbitrage, the current price P_t of any asset is given by the expectation of the future asset payoff X_T at time $T = t + \tau$ multiplied by the pricing kernel $m_{t,T}$:

$$P_t = \mathbb{E}^{\mathbb{P}}[m_{t,T} X_T | \mathcal{F}_t] \equiv \int X_T(s)\, m_{t,T}(s)\, \pi^{\mathbb{P}}_{t,T}(s)\, ds, \tag{1}$$

where s represents the state of the economy, $\mathcal{F}_t$ is the information available to investors at time t and $\pi^{\mathbb{P}}_{t,T}(s)$ is the probability density function (PDF) under the physical measure $\mathbb{P}_t$. The pricing kernel distorts the physical measure as to reflect investors' compensation for risk, such that one can take simple expectations to calculate the price of any asset.

More specifically, given the almost sure positivity of $m_{t,T}$ under no-arbitrage, the pricing kernel induces a change of measure from the physical measure $\mathbb{P}_t$ to the risk-neutral measure $\mathbb{Q}_t$. Given a risk-free rate R_f from t to T, this can be seen by noting that $\mathbb{E}_t[m_{t,T}] = 1/R_f$, and dividing and multiplying (1) by $\mathbb{E}_t[m_{t,T}]$:

$$P_t = \frac{1}{R_f} \int X_T(s)\, \frac{m_{t,T}(s)}{\mathbb{E}_t[m_{t,T}]}\, \pi^{\mathbb{P}}_{t,T}(s)\, ds = \frac{1}{R_f} \int X_T(s)\, \pi^{\mathbb{Q}}_{t,T}(s)\, ds \equiv \frac{1}{R_f} \mathbb{E}^{\mathbb{Q}}[X_T | \mathcal{F}_t], \tag{2}$$

where $\pi^{\mathbb{Q}}_{t,T}(s)$ is the PDF under the risk-neutral measure $\mathbb{Q}_t$. This PDF is often called the state-price density, as it defines the (forward) prices of Arrow-Debreu securities paying one dollar at time T if state of nature s is realized, and zero elsewhere. In contrast, $\pi^{\mathbb{P}}_{t,T}(s)$ can be interpreted as the expected payoff of an Arrow-Debreu security for state s.

From (1) and (2), it becomes evident that the pricing kernel is the ratio of discounted risk-neutral probabilities and physical probabilities:

$$m_{t,T}(s) = \frac{1}{R_f} \frac{\pi^{\mathbb{Q}}_{t,T}(s)}{\pi^{\mathbb{P}}_{t,T}(s)}. \tag{3}$$

The economy-wide pricing kernel above depends on the realization of the state s of the economy. However, there is no consensus among researchers on which are the relevant state variables to consider from a modeling perspective.

As an alternative, a large strand of the literature, starting with Jackwerth (2000), Aït-Sahalia and Lo (2000) and Rosenberg and Engle (2002), has proposed to focus instead on the projection of the pricing kernel onto states $R_{t,T}$ of the market return:

$$m_{t,T}(R_{t,T}) = \frac{1}{R_f} \frac{\pi^{\mathbb{Q}}_{t,T}(R_{t,T})}{\pi^{\mathbb{P}}_{t,T}(R_{t,T})}. \tag{4}$$

The main advantage is that this projection can be estimated using S&P 500 options and the time series of market returns. On the one hand, the seminal result of Breeden and Litzenberger (1978) allows to recover from option prices across different strikes the risk-neutral distribution of underlying returns over the maturity τ of the options, $\pi^{\mathbb{Q}}_{t,T}(R_{t,T})$. On the other hand, historical market returns are informative about the physical distribution $\pi^{\mathbb{P}}_{t,T}(R_{t,T})$.[6] Importantly, $m_{t,T}(R_{t,T})$ has the same pricing implications as the economy-wide pricing kernel $m_{t,T}(s)$ for assets with payoffs that depend only on $R_{t,T}$.

The focus on the projection of the pricing kernel onto S&P 500 returns is also justified by the general interest in learning about investors' risk preferences towards the market index and associated equity and variance risk premia. In particular, if one assumes that the market index is equal to the aggregate wealth and a representative agent exists, $m_{t,T}(R_{t,T})$ is the marginal utility of this agent. Under this interpretation, the pricing kernel should be monotonically decreasing in market returns if the representative agent is risk-averse. However, the literature provides extensive evidence for monthly or longer horizons that $m_{t,T}(R_{t,T})$ is usually a nonmonotonic (generally U-shaped) function of market returns instead, characterizing the pricing kernel puzzle (Cuesdeanu and Jackwerth,

[6]There is a potential mismatch of conditioning information sets when estimating $\pi^{\mathbb{Q}}_{t,T}(R_{t,T})$ with option prices, that are forward-looking, and $\pi^{\mathbb{P}}_{t,T}(R_{t,T})$ with historical returns, that are backward-looking (see, e.g., Linn, Shive, and Shumway, 2018). We discuss how we handle that empirically in Section 3.4.

2018).[7] In the next subsections, we discuss how various objects of interest in our analysis relate to the pricing kernel and its shape.

2.2 Expected option returns

The shape of the pricing kernel has direct implications for expected option returns. The expected return of a call option can be defined as below:[8]

$$\mu_t^c(S_t, R_{t,T}, K) = \frac{\mathbb{E}_t[\max(S_t R_{t,T} - K, 0)]}{\mathbb{E}_t[\max(S_t R_{t,T} - K, 0)\, m_{t,T}(R_{t,T})]} - 1, \tag{5}$$

where S_t is the market index at t and K is the option strike price. The expected return of a put option is analogously defined for the payoff $\max(K - S_t R_{t,T}, 0)$. The numerator in (5) is the expected payoff of the option under the physical measure, while the denominator is the expected payoff under the risk-neutral measure, i.e., the option price.

Coval and Shumway (2001) show that if $m_{t,T}(R_{t,T})$ is monotonically decreasing, calls (puts) have expected returns that are positive (negative) and increase with the strike price. Intuitively, a monotonically decreasing $m_{t,T}(R_{t,T})$ shifts probability mass towards states where the call (put) is less (more) valuable. Therefore, as the strike increases, the call price decreases by more than the expected payoff, increasing the expected return. Conversely, as the strike decreases, the put price decreases by less than the expected payoff, decreasing the expected return. If, instead, the pricing kernel is a U-shaped function of returns (i.e., increasing for some region of positive returns), Bakshi et al. (2010) show that expected call returns are decreasing in the strike and negative beyond a strike threshold. This is because $m_{t,T}(R_{t,T})$ shifts probability mass towards states where the call option is more valuable, such that the call price decreases by less than the

[7] More recently, Almeida and Freire (2023) show that if one interprets $m_{t,T}(R_{t,T})$ as representing the preferences of a marginal agent in the option market instead of a representative investor, a nonmonotonic shape is not puzzling but rather reflects the risk exposures from the marginal agent's options positions.

[8] To see that, note that $\mathbb{E}_t[\frac{\max(S_t R_{t,T} - K, 0)}{\mathbb{E}_t[\max(S_t R_{t,T} - K, 0)\, m_{t,T}(R_{t,T})]}] = \frac{\mathbb{E}_t[\max(S_t R_{t,T} - K, 0)]}{\mathbb{E}_t[\max(S_t R_{t,T} - K, 0)\, m_{t,T}(R_{t,T})]}$.

expected payoff as the strike increases, decreasing the expected return.[9]

2.3 Equity premium

The shape of $m_{t,T}(R_{t,T})$, or, equivalently, how $\pi^{\mathbb{Q}}_{t,T}(R_{t,T})$ relates to $\pi^{\mathbb{P}}_{t,T}(R_{t,T})$, is informative about which return states are compensated via the equity premium. To see that, first note that the conditional equity premium can be written as:

$$\mathbb{E}_t[R_{t,T}] - R_f = \int_0^{\infty} R_{t,T}[\pi^{\mathbb{P}}_{t,T}(R_{t,T}) - \pi^{\mathbb{Q}}_{t,T}(R_{t,T})]dR_{t,T}. \tag{6}$$

To decompose the unconditional equity premium, Beason and Schreindorfer (2022) take the unconditional expectation of (6) and consider net market returns $\tilde{R} = R - 1$ to define:

$$EP(x) = \frac{\int_{-1}^{x} \tilde{R}\,[\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R})]d\tilde{R}}{\int_{-1}^{\infty} \tilde{R}\,[\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R})]d\tilde{R}}, \tag{7}$$

where $\pi^{\mathbb{P}}(\tilde{R}) = \mathbb{E}[\pi^{\mathbb{P}}_{t,T}(\tilde{R}_{t,T})]$ and $\pi^{\mathbb{Q}}(\tilde{R}) = \mathbb{E}[\pi^{\mathbb{Q}}_{t,T}(\tilde{R}_{t,T})]$. $EP(x)$ measures the fraction of the average equity premium that is associated with market returns below x.

Returns around zero contribute only marginally to the equity premium (as $\tilde{R} \approx 0$), such that $EP(x)$ is expected to be flat around those states. Outside this region, the shape of the $EP(x)$ function will depend on the shape of the (average) pricing kernel. Under a monotonically decreasing pricing kernel, every state $\tilde{R}$ contributes positively to the equity premium, i.e., $EP(x)$ is always increasing. To see that, note that in the negative return region, $\tilde{R} < 0$ and the pricing kernel is above 1, which means that $\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R}) < 0$, such that $\tilde{R}\,[\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R})] > 0$ and $EP(x)$ is increasing. Analogously, in the positive return region, $\tilde{R} > 0$ and the pricing kernel is below 1, which means that $\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R}) > 0$, such that $\tilde{R}\,[\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R})] > 0$ and $EP(x)$ is again increasing. Now, if we consider instead a U-shaped pricing kernel where $\pi^{\mathbb{Q}}(\tilde{R})$ is above $\pi^{\mathbb{P}}(\tilde{R})$ (i.e., pricing kernel is

[9] Since a U-shaped pricing kernel is declining in the region of negative market returns, the implications for expected put returns are the same as under a monotonically decreasing shape.

above 1) for some positive return $\tilde{R} > 0$, then $\tilde{R}\,[\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R})] < 0$ and $EP(x)$ is decreasing, i.e., such positive returns contribute negatively to the equity premium.

We give a new economic interpretation for these relations, which is as follows. For each state $\tilde{R}$, consider the asset that pays $\tilde{R}$ in this state and zero otherwise, i.e., the asset defined by buying $\tilde{R}$ units of the Arrow-Debreu security of state $\tilde{R}$. Then, $\tilde{R}\,[\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R})]$ is the expected payoff minus the price of this asset. If the pricing kernel is monotonically decreasing, these assets have a low (high) payoff when the pricing kernel is high (low), such that they are speculative assets with a positive expected return, i.e., $\tilde{R}\,[\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R})] > 0$. In other words, investors would require compensation for holding any of these assets, such that all states contribute positively to the equity premium. In contrast, if there is a U-shape where the pricing kernel is high for a region of positive returns, the assets in this region will have a high payoff when the pricing kernel is high, such that they are hedging assets with a negative expected return, i.e., $\tilde{R}\,[\pi^{\mathbb{P}}(\tilde{R}) - \pi^{\mathbb{Q}}(\tilde{R})] < 0$. That is, investors would be willing to give up compensation to hedge against these states, such that they contribute negatively to the equity premium.

2.4 Variance risk premium

The pricing kernel projection onto market returns is also informative about the magnitude of the variance risk premium. Defined as the difference between the risk-neutral and physical expected variance of the market return over horizon τ, it reflects the compensation investors require for bearing variance risk (Bollerslev et al., 2009). Baele, Driessen, Ebert, Londono, and Spalt (2019) demonstrate that the variance risk premium is closely related to expected option returns. In particular, it can be written as a weighted average of expected returns of put and call options across strikes, with negative weights. Consequently, the variance risk premium is higher under a U-shaped pricing kernel, where both call and put expected returns are negative, than under a monotonically decreasing pricing kernel. Intuitively, this premium reflects compensation for extreme negative and positive return states, such that this compensation is higher when $m_{t,T}(R_{t,T})$ is U-shaped.

It is also possible to decompose the total variance risk premium into the specific compensation for variation risk in positive and negative market returns (Kilic and Shaliastovich, 2019). Analogously to above, the risk premium for positive (negative) return variation is a weighted average of expected call (put) returns, with negative weights. If the pricing kernel is monotonically decreasing (U-shaped), expected call returns are positive (mostly negative) and the positive return variation premium is negative (positive).[10] That is, if marginal utility is high for positive market returns, investors would be willing to pay a premium to be protected against large positive returns. On the other hand, the more negative expected put returns are, the steeper is the pricing kernel for negative returns and the higher is the compensation for negative return variation.

The expected returns of specific option strategies contain further information about the variance risk premium. Bakshi and Kapadia (2003) and Coval and Shumway (2001) show, respectively, that negative delta-hedged option returns and negative straddle returns reflect a positive variance risk premium. These strategies profit from (and are a hedge against) increases in market volatility, such that a negative expected return indicates that investors are willing to pay a premium to be protected against variance risk.

2.5 Option price bounds

The shape of $m_{t,T}(R_{t,T})$ tells us how option prices are jointly reconciled with the physical distribution implied by market returns. A related, but alternative way of investigating this relation is by comparing each observed option price with option price bounds consistent with the physical distribution $\pi^{\mathbb{P}}_{t,T}(R_{t,T})$ and specific risk preferences.

[10]More precisely, under a U-shaped pricing kernel, expected call returns are only negative beyond a strike that depends on how pronounced the U-shape is. Therefore, if the pricing kernel is only mildly U-shaped, it can still be the case that expected call returns are mostly positive and the positive return variation premium is negative.

Of particular interest for us are the second-order stochastic dominance (SSD) bounds (Levy, 1985; Perrakis and Ryan, 1984; Ritchken, 1985), which provide the maximum and minimum price for a given option consistent with risk-averse investors trading in the underlying asset and the risk-free rate. In other words, these bounds allow for market segmentation by giving all option prices compatible with the set of pricing kernels that are monotonically decreasing in the market returns.

A violation of the SSD lower (upper) bound by a given option means that any risk-averse investor can improve expected utility by taking a long (short) position in the option, or, equivalently, that the option dominates (is dominated by) the underlying asset by second-order stochastic dominance. That is, a violation would mean that there is no marginal investor in the index, risk-free rate and the option with a monotonically decreasing pricing kernel (i.e., satisfying risk aversion). This option is often regarded as "mispriced" as its price cannot be reconciled with the physical distribution under reasonable risk preferences.

It is important to note that SSD bounds offer related, but complementary insights relative to the pricing kernel in (4). If $m_{t,T}(R_{t,T})$ is monotonically decreasing, then this pricing kernel is part of the SSD admissible set and the option prices will be inside the SSD bounds. In contrast, if $m_{t,T}(R_{t,T})$ is nonmonotonic, this means that no unique monotonically decreasing pricing kernel prices all options, but it is still possible that different monotonically decreasing pricing kernels price the different options in the cross-section. Conversely, if option prices satisfy SSD bounds, this does not mean that $m_{t,T}(R_{t,T})$ is monotonically decreasing, whereas if they violate the bounds, this implies that $m_{t,T}(R_{t,T})$ is nonmonotonic. In fact, while empirical evidence favors a U-shaped pricing kernel projection at the one-month horizon, Almeida and Freire (2022) show that S&P 500 option prices generally satisfy SSD bounds, where options with different moneyness require heterogeneous investors who differ in their assessment of tail risk to be priced.[11]

2.6 Empirical strategy

The theoretical framework described above provides insights into investors' risk preferences over the horizon τ corresponding to the maturity of the options used. Most of the literature applying these methods has focused on the one-month horizon or longer, partially motivated by the liquidity of the associated options. However, as previously described, the option market has changed dramatically over the last few years. Now, the most traded contracts are 0DTE options, which give investors the opportunity to hedge against or make leveraged bets on specific market movements over the day. As such, 0DTEs are a valuable source of information about risk premia and compensation for risk at intra-daily horizons. We aim to extract and analyze this information.

For the 0DTEs, we will consider different times of the day for t, while T will always be the market close, which is usually at 16:00. More specifically, our analysis will be based on the cross-section of 0DTEs at 10:00, 10:30, 11:00, 11:30, 12:00, 12:30, 13:00, 13:30 and 14:00, such that the horizon/option maturity τ will be 6, 5.5, 5, 4.5, 4, 3.5, 3, 2.5 and 2 hours, respectively. In the next section, we show that this range of times of the day is where the relative option bid-ask spread is reasonably stable at its minimum over the day. For each of those times of the day, we will estimate the pricing kernel in (4), calculate option returns of different strategies (from t to T), decompose the corresponding equity premium, estimate the variance risk premium and compute SSD bounds for each option. For comparison, we will also consider options with maturities ranging from 1 to 22 business days, i.e., from 1 to 22DTE.

[11] This evidence differs from that by Constantinides, Jackwerth, and Perrakis (2009), who find substantial violations of SSD bounds in the S&P 500 option market. The main reason for this difference is that the conditional physical distribution they estimate keeps the volatility constant over long periods of time, during which volatility varies considerably. In contrast, Almeida and Freire (2022) adjust volatility daily in the estimation of the conditional physical distribution.

3 Data description and implementation details

3.1 Data

We obtain the intra-day S&P 500 option data from CBOE, which includes bid and ask quotes, trading volume, open interest and underlying asset price at 1-minute intervals. We define the price of an option as the bid and ask midpoint. We select all dates between January 6 2012 and March 18 2025 for which 0DTE SPXW options are available. The first weeklies were introduced by CBOE on October 28 2005 with Friday expirations. Wednesday, Monday, Tuesday and Thursday expirations followed with introduction dates February 23 2016, August 15 2016, April 18 2022 and May 11 2022, respectively. This means that our sample contains one day per week up until February 23 2016, then two days per week until August 15 2016, three days per week until April 18 2022, four days per week until May 11 2022, and all days of the week afterwards. We have 1,815 dates in total, where roughly 40% of those dates are between May 11 2022 and March 18 2025.

Figure 1 depicts the striking evolution of the 0DTE option market over the last years in terms of its fraction of trading volume relative to the entire S&P 500 option market. While 0DTEs accounted for only around 2% of total trading volume in 2012, today they represent more than 50% of the entire option market and are the most traded maturity. As noted by Bandi et al. (2023), this corresponds to a daily notional dollar volume of around 1 trillion dollars. This meteoric increase can partially be explained by the daily availability of 0DTE options since May 2022, allowing investors to hedge and make leveraged bets on specific intra-daily market movements for any day of the week.

To filter the raw option data, we aim to avoid as much as possible options with small trading volume and zero bid, while also selecting a comparable set of strikes over time. What mainly defines the range of strikes being traded on a given day is volatility: on days where volatility is high (low), large return realizations are more (less) likely to occur, such that investors trade options for a larger (smaller) range of strikes. For this reason, we classify options in terms of their standardized log-moneyness $k_{std} = \frac{\log(K/S_t)}{\sigma_{BS}(0)\sqrt{\tau}}$, which controls for the level of volatility as $\sigma_{BS}(0)$ is the ATM implied volatility for time of the day t and maturity τ.

By analyzing the 0DTE option data, we identify that the range of k_{std} between -6 and 3 strikes a good balance between trading volume and low proportion of zero bids. This can be visualized in the upper subplots of Figure 2, which report, for different times of the day and bins of k_{std}, the average trading volume and proportion of contracts with zero bid over time. As can be seen, the bulk of trading volume is within the k_{std} range of -6 and 3, whereas the volume outside this interval is negligible. At the same time, zero bids are essentially inexistent for $k_{std} \in [-3, 2]$ and then occur increasingly more for more extreme moneyness levels. Our interval of $[-6, 3]$ avoids the extremely large proportion of zero bids of deeper OTM put and call options. From this interval, we further drop observations that have both zero volume and zero bid.

The bottom subplots of Figure 2 further display the average implied volatilities (IVs) and average number of strikes for each bin. For all times of the day, 0DTE IVs display a smile across moneyness, where OTM puts and calls are equally expensive in terms of IV. This is in contrast to the usual smirk observed for longer-maturity S&P 500 options (where IVs are much higher for OTM puts than for OTM calls). The average IVs outside $k_{std} \in [-6, 6]$ are extremely high, which highlights the importance of excluding these options that are not traded and would contaminate results.[12] As for the average number of strikes, it is approximately constant across moneyness bins and decreases from around 4 at 10:00 to 2 strikes per bin at 14:00.

Having defined our option sample, we proceed to choose a set of times of the day

[12] IVs outside $k_{std} \in [-6, 6]$ are that high due to the deeper OTM options that have very small, but still positive prices, while the probability of returns occurring such that they finish in-the-money is virtually zero. Since these deeper OTM options are not traded, their extremely high IVs are artificial and do not reflect market expectations.

for our analysis with the goal of being representative while feasible to report results. To guide our choice, Figure 3 reports, for our option sample, the 0DTE trading volume and relative bid-ask spread over the day. While trading volume is higher at market open and close, these times of the day are also the ones with highest bid-ask spread over the day. The bid-ask spread tends to be relatively stable at its minimum between 10:00 and 14:00. For this reason, we select this range of times of the day for our analysis, with intervals of 30 minutes to keep it feasible to report the results.

Throughout our analysis, we also use data for longer DTEs ranging from 1 to 22 business days. For these options, we always observe them at the market close, for all dates that they are available between January 6 2012 and March 18 2025. For ease of comparison with our 0DTE results, for each longer DTE, we select the options with standardized log-moneyness between -6 and 3, and drop observations with both zero volume and zero bid. For each maturity, we extract the dividend yield that makes the put-call parity satisfied for the ATM call and put. Finally, we obtain high-frequency data on the S&P 500 index, spanning January 1996 to March 2025, from Refinitiv Tick History. The risk-free rate, which we obtain for the same sample period, is the daily one-month Treasury bill rate from the FRED (Federal Reserve Bank of St. Louis) website. We assume that the risk-free rate remains constant throughout the day.

3.2 Option returns

For a given day in our sample and time of the day t, we compute hold-until-maturity returns of different portfolios of options expiring at the end of the day. We first calculate the return of the call (put) option with price $O^c_{t,T}$ ($O^p_{t,T}$) and strike K as:

$$R_c = \frac{\max(S_T - K, 0)}{O^c_{t,T}} - 1, \quad R_p = \frac{\max(K - S_T, 0)}{O^p_{t,T}} - 1, \tag{8}$$

where S_T is the market index at the option expiration. We will analyze how call and put returns vary with the strike price over our sample, which is informative about the shape of the pricing kernel. To have returns of options with the same moneyness for each day of our sample, we select the option with moneyness closest to a given target value.

Then, we compute the returns of different option strategies that are insightful about the variance risk premium. First, we consider simple straddle returns obtained from the simultaneous purchase of an ATM call and ATM put with strike K:

$$\text{Simple-Straddle} = \frac{\max(S_T - K, 0) + \max(K - S_T, 0)}{O^c_{t,T} + O^p_{t,T}} - 1. \tag{9}$$

We focus on the ATM straddle that is more exposed to volatility risk. In addition, we calculate the return of an exactly delta-neutral ATM straddle:

$$\text{Straddle} = wR_c + (1-w)R_p, \quad w = -\frac{\Delta_p / O^p_{t,T}}{\Delta_c / O^c_{t,T} - \Delta_p / O^p_{t,T}}, \tag{10}$$

where Δ_c (Δ_p) is the call (put) Black-Scholes delta.

Finally, we follow Bakshi and Kapadia (2003) by calculating ATM delta-hedged call returns as:[13]

$$\Delta\text{-Hedged} = \frac{\max(S_T - K, 0) - O^c_{t,T} - \Delta_c(S_T - S_t) - r^f_t (O^c_{t,T} - \Delta_c S_t) \times \frac{\tau}{(24\times 365)}}{S_t}, \tag{11}$$

where r^f_t is the annualized risk-free rate and τ is the time to maturity expressed in hours, e.g., $\tau = 6$. Since the straddle and delta-hedged strategies are essentially long positions in market volatility, we will analyze their average returns over our sample to extract information about the variance risk premium over the day. For these strategies, we use the observed price of the option closest to ATM.

[13] Results are very similar if, instead of the underlying price S_t, we set the denominator to be the initial investment absolute cost $|O^c_{t,T} - \Delta_c S_t|$.

3.3 Risk-neutral distribution

For a given day of our sample and time of the day, we estimate the risk-neutral distribution from the cross-section of 0DTE option prices. Breeden and Litzenberger (1978) show that, under no-arbitrage and in the presence of a continuum of options across strikes, risk-neutral probabilities are equal to the risk-free rate times the second derivative of option prices with respect to the strike price:

$$\pi_{t,T}^{\mathbb{Q}}(R_{t,T}) = S_t \times R_f \times \left. \frac{\partial^2 O_{t,T}^c(K)}{\partial K^2} \right|_{K=S_T}, \tag{12}$$

where the strikes represent different states of the underlying asset price at maturity and multiplying by S_t performs a change of variables from $\pi_{t,T}^{\mathbb{Q}}(S_T)$ to $\pi_{t,T}^{\mathbb{Q}}(R_{t,T})$.

In practice, however, we only observe a discrete set of strikes that sometimes does not cover the whole range of moneyness. For this reason, it is necessary to interpolate and extrapolate observed option prices to compute the derivative and estimate $\pi_{t,T}^{\mathbb{Q}}(R_{t,T})$. To do so, we follow the standard practice in the literature of converting option prices to IVs using the Black and Scholes (1973) formula, fitting an interpolant to them, using the interpolant to generate IVs for a fine grid of strikes, translating IVs back to option prices, and computing (12) over the fine grid of strikes via finite differences.[14] Only OTM options are used to fit the interpolant, as they are more liquid than in-the-money (ITM) options, which should contain redundant information by put-call parity.

We fit the IV curve across strikes using the parsimonious Stochastic Volatility Inspired (SVI) method of Gatheral (2004). This method has also been used by Beason and Schreindorfer (2022) to estimate the risk-neutral distribution and combines reliable interpolation of the IV curve with well-behaved extrapolation for extreme moneyness levels.

[14] It is important to emphasize that this approach does not assume that the Black and Scholes (1973) model is valid. Rather, the Black and Scholes (1973) formula is only used as a one-to-one mapping between option prices and IVs. This is done because fitting the IV curve is much easier than fitting option prices as IVs are comparable across strikes.

More specifically, the SVI describes the square of IV with the function:

$$\sigma^2_{BS}(k) = a + b\left\{\rho(k-m) + \sqrt{(k-m)^2 + \sigma^2}\right\}, \tag{13}$$

where $k = \log(K/S_t)$ is the log-moneyness and a, b, ρ, m and σ are parameters.[15] We fit (13) to the cross-section of observed IVs for a given DTE and estimate the parameters by minimizing the mean squared error with a constrained nonlinear programming solver.[16]

Figure OA.1 plots, for a representative date of our sample and different maturities, the observed IVs and the fitted IVs using the SVI method. The SVI provides an overall excellent fit, with average OLS R^2's higher than 90%. This, in turn, results in well-behaved risk-neutral distributions, as can be seen in Figure OA.2 for the same representative day. These distributions are obtained by interpolating and extrapolating the IVs in a grid using the SVI method, mapping the IVs back to option prices and then computing $\pi^{\mathbb{Q}}_{t,T}(R_{t,T})$ via the Breeden and Litzenberger (1978) formula. The plot shows for 0DTEs how the broad range of standardized log-moneyness we consider translates to a narrow range of return states that investors believe the market can experience over this particular day. As the time gets closer to market close, the risk-neutral distribution gets narrower, reflecting that there is less room for large return realizations.

3.4 Physical distribution

To calculate the pricing kernel projection and the SSD option price bounds, we need to estimate the conditional physical distribution $\pi^{\mathbb{P}}_{t,T}(R_{t,T})$. Aït-Sahalia and Lo (2000) and Jackwerth (2000) rely directly on the historical market return distribution, where there is

[15] More specifically, a controls the IV level, b the IV slope, ρ the asymmetry of the IV slope for negative and positive k, m the horizontal location of the IV curve, and σ the ATM curvature of the IV curve.

[16] The SVI is well defined for $a \in \mathbb{R}$, $b \geq 0$, $|\rho| \leq 1$, $m \in \mathbb{R}$, $\sigma > 0$ and $a + b\,\sigma\sqrt{1-\rho^2} \geq 0$. We impose these constraints in the optimization, with two small modifications: we replace $a + b\,\sigma\sqrt{1-\rho^2} \geq 0$ with the slightly stronger restriction $a \geq 0$, which yields better behaved extrapolations for the right tail, and we impose $\sigma \geq 0.01$, which helps discipline the IV ATM curvature.

a trade-off between using a short sample, which makes the distribution conditional, and using a long sample, which improves the estimation precision, especially for the tails. A more recent approach has been to take the unconditional return distribution from a long sample and make it conditional by adjusting for the conditional volatility at time t using GARCH models (see, e.g., Barone-Adesi, Engle, and Mancini, 2008). This preserves the empirical patterns of skewness, kurtosis, and tail probabilities, but has the drawback that GARCH models can be misspecified. Even if one uses realized variance instead to make the distribution conditional, there is still a potential mismatch of conditioning sets in comparing backward-looking information from historical returns with forward-looking information from option prices (see, e.g., Linn et al., 2018).

We follow a similar approach to Almeida and Freire (2022) to overcome the issues above. For a given day in our sample and DTE, we first estimate the historical return distribution as the histogram of past market returns from t to T over a long sample starting on January 1996.[17] Then, we make the return distribution conditional by setting its volatility equal to the ATM IV at time t of the current day, which is forward-looking. That is, we use minimal option information to make the conditioning sets of $\pi^{\mathbb{P}}_{t,T}(R_{t,T})$ and $\pi^{\mathbb{Q}}_{t,T}(R_{t,T})$ comparable. While the ATM IV contains a risk premium, other papers such as Dew-Becker, Giglio, and Kelly (2021) also use it as a proxy for the expected physical volatility given its good performance in forecasting future realized volatility.

The resulting conditional physical distribution is an unsmoothed histogram. For the purpose of estimating the pricing kernel projection, it is necessary to smooth it to obtain a well-behaved PDF. We follow Jackwerth (2000) in fitting a kernel density with a Gaussian kernel to smooth the histogram and obtain $\pi^{\mathbb{P}}_{t,T}(R_{t,T})$.[18] Figure OA.2 displays, for a

[17]Following Almeida and Freire (2022), we also impose the sensible economic restriction of a 5% lower bound on the annualized equity premium over the risk-free rate. That is, if the annualized mean of the unconditional return distribution generates a premium less than 5% over the risk-free rate, we demean the returns and reintroduce a 5% equity premium. Jackwerth (2000) imposes a similar restriction.

[18]For a given day, the obtained histogram is smoothed with a Gaussian kernel with bandwidth $\frac{x\sigma}{\sqrt[m]{n}}$,

representative date of our sample, the conditional physical distribution together with the risk-neutral distribution for different horizons. The (discounted) ratio between the risk-neutral and physical PDFs gives the estimate of the pricing kernel projection $m_{t,T}(R_{t,T})$ for that day and horizon.

3.5 SSD bounds and risk premia

Using the estimated physical distribution, we compute, for each call option with strike K, the following SSD upper and lower price bounds as in Ritchken (1985):[19]

$$C_{\max} = \mathbb{E}[\max(S_t R_{t,T} - K, 0)]/\mathbb{E}[R_{t,T}], \tag{14}$$

$$C_{\min} = \mathbb{E}[\max(S_t R_{t,T} - K, 0)|S_t R_{t,T} < s_j^*]\,\frac{1}{R_f}, \tag{15}$$

where s_j^* is chosen such that $\mathbb{E}[S_t R_{t,T}|S_t R_{t,T} < s_j^*] = S_t R_f$. All expectations are calculated under the estimated $\pi^{\mathbb{P}}_{t,T}(R_{t,T})$ over the grid of states $R_{t,T}$. Equation (14) says that the maximum price of the call should be the price such that the expected call return equals the expected return on the market. The interpretation for the lower bound is less straightforward. Ritchken (1985) uses linear programming techniques to show that these bounds contain all prices for the call option consistent with the set of pricing kernels that are monotonically decreasing in $R_{t,T}$. The bounds for the put option with strike K can be obtained via put-call parity. We will compare the bounds to the observed option prices to identify any potential mispricing of the 0DTEs.

We follow Beason and Schreindorfer (2022) to implement the decomposition of the unconditional equity premium as in (7). First, we estimate the unconditional risk-neutral distribution $\pi^{\mathbb{Q}}(\tilde{R})$ over our sample as the average of the conditional risk-neutral dis-

where σ is the volatility of the return distribution, n is the number of observations, and we set $x = 1.8$ and $m = 5$, which strikes a good balance between smoothness and fit.

[19] Perrakis and Ryan (1984) and Levy (1985) derive the same bounds following different approaches.

tributions, i.e., the average of $\pi^{\mathbb{Q}}_{t,T}(\tilde{R}_{t,T})$ state by state. With that, we can evaluate $\int_{-1}^{\infty} \tilde{R}\pi^{\mathbb{Q}}(\tilde{R})d\tilde{R}$ numerically over the grid of $\tilde{R}$ (which is equal to the grid of $R_{t,T} - 1$). Then, we compute $\int_{-1}^{\infty} \tilde{R}\pi^{\mathbb{P}}(\tilde{R})d\tilde{R}$ from the unconditional empirical distribution of market returns (of the horizon of the option) over our sample as $(1/\mathcal{T})\sum_{i=1}^{\mathcal{T}} \tilde{R}_{i,t,T}\mathbf{1}\{\tilde{R}_{i,t,T} \leq x\}$, where $\mathcal{T}$ denotes the total number of days, $\tilde{R}_{i,t,T}$ is the realized market return of day i from time of the day t to horizon T, and we consider x's over the grid of $\tilde{R}$. This is equivalent to computing the integral under the unconditional physical distribution.

Finally, we compute a measure of the variance risk premium similarly to Bollerslev et al. (2009). They calculate it for the one-month horizon as the risk-neutral expected variance over the next month minus the physical expected variance proxied by the realized variance from the previous month to the current one. Analogously, our ex-ante variance risk premium $VRP_{t,T}$ from time t to T is the expected risk-neutral variance implied by the cross-section of 0DTEs at time t minus the realized variance from t to T of the previous day.[20] The expected risk-neutral variance is computed as in Bakshi et al. (2003):

$$V^{\mathbb{Q}}_{t,T} = \int_{S_t}^{\infty} \frac{2[1 - \log(K/S_t)]}{K^2} O^{c}_{t,T}(K)dK + \int_{0}^{S_t} \frac{2[1 + \log(S_t/K)]}{K^2} O^{p}_{t,T}(K)dK, \tag{16}$$

where we compute the integrals using the interpolated and extrapolated option prices from the SVI method. The realized variance (Andersen, Bollerslev, Diebold, and Labys, 2003) $RV_{t,T}$ is the sum of 1-minute squared log-returns on the market index. To disentangle the compensation demanded by investors to bear variation risk in positive and negative market returns, we also compute the "good" and the "bad" variance risk premium in the spirit of Kilic and Shaliastovich (2019). The former (latter), $VRP^{+}_{t,T}$ ($VRP^{-}_{t,T}$), is defined as the first (second) integral in (16) minus the sum of 1-minute squared market returns times an indicator function for a positive (negative) return. Naturally, $VRP_{t,T} = VRP^{+}_{t,T} + VRP^{-}_{t,T}$.

[20]For longer DTEs, the realized variance is computed from day $t - T$ to t.

4 Empirical results

4.1 Average option returns

We start by analyzing the returns of different option strategies. Figures 4 and 5 plot the average over our sample of call and put returns across strikes, respectively, together with 90% i.i.d. bootstrap confidence bands, for different maturities.[21] Focusing first on the 0DTEs, observed patterns are similar across different times of the day. Call options experience low returns overall, which are decreasing with the strike starting from the ATM region and eventually become highly negative with statistical significance. Following the rationale of Bakshi et al. (2010), this provides evidence that the intra-day pricing kernel is increasing in a region of positive return states. In other words, writing naked OTM calls is usually profitable in the 0DTE option market, which would be aligned with investors requiring compensation for bearing positive return variation risk. As for put options, average returns are always negative, with statistical significance for OTM puts. This is consistent with a monotonically decreasing pricing kernel in the region of negative market returns, reflecting investors' aversion to downside risk. Again, writing naked OTM puts is usually a profitable strategy, compatible with compensation for negative return variation risk. Importantly, average OTM call returns are more negative than OTM put returns, suggesting more compensation for upside than downside risk.

For longer maturities, average OTM call returns are less negative than for 0DTEs. In fact, for one-month options, average call returns are mostly positive and increasing in the strike, and negative values for deep OTM calls are insignificant. This suggests that nonmonotonicity in the pricing kernel over the positive return region gets less pronounced as maturity increases. In contrast, average OTM put returns are more negative for 1-22

[21] Due to the small dollar prices of 0DTE options, for a few days returns can be quite extreme. To minimize the effect of these outliers and produce a smoother plot, for each moneyness we winsorize the right-tail of the time-series of 0DTE option returns at 0.5%. This has no qualitative effect on the conclusions we obtain from the average returns.

DTEs than 0DTEs, reflecting stronger compensation for downside risk. This is such that, over longer horizons, compensation for negative return variation risk dominates that for positive return variation risk.

We further consider the returns of ATM delta-hedged call options, straddles and delta-neutral straddles. Figure 6 displays their average returns together with 90% i.i.d. bootstrap confidence bands for different tenors.[22] All 0DTE strategies produce negative average returns. Since these strategies are essentially long positions in volatility, a negative average return indicates that investors are willing to pay a premium to be protected against variance risk over the day. On the other hand, an investor willing to be exposed to this risk would profit, on average, from shorting delta-hedged calls and straddles in the 0DTE market. The confidence bands indicate that the statistical significance of the negative average returns is stronger from 12:00 to 14:00. The evidence is similar for longer maturities, with negative average returns indicating a positive variance risk premium, which are statistically significant for all maturities except for 22DTEs.

4.2 Risk premia

We now investigate the implications of 0DTE options for intra-day market risk premia. Panel (a) of Figure 7 plots the decomposition of the equity premium across return states for different times of the day. Most of the equity premium stems from compensation to market returns between -5% and 0%. Strikingly, these states account for 300% (800%) of the total equity premium from 10:00 (14:00) to close, which would amount to an annualized premium of 50% (150%), as seen in the right axis of the plot. More important than the magnitude of these values, however, is the reason why they exceed 100%: positive market returns contribute negatively to the equity premium. This is consistent with a U-shaped pricing kernel, as discussed in Section 2.3. Since marginal utility is high for

[22] To alleviate the effects of outliers associated with Covid, we winsorize the right-tail of the returns.

positive market returns, investors are willing to pay a premium to hold Arrow-Debreu securities paying in these states, such that they have a negative contribution to the equity premium. That is, the intra-day equity premium, which is around 15% annualized over our sample, would be much higher if the pricing kernel were monotonically decreasing.

For comparison, Panel (b) of Figure 7 depicts the equity premium decomposition for longer horizons as implied by 1 to 22 DTEs. As can be seen, the negative contribution of positive market return states to the equity premium decreases as the maturity lengthens, consistent with pricing kernel nonmonotonicity becoming less pronounced. For the one-month horizon, returns between -30% and -10% account for half of the equity premium, whereas positive returns between 0% and 5% account for the other half. The fact that positive returns contribute positively to the equity premium suggests that marginal utility is relatively low for these states, i.e., the U-shape is less pronounced for this maturity.[23]

We next estimate, for each day and maturity, the $VRP_{t,T}$ and its two components, $VRP_{t,T}^{+}$ and $VRP_{t,T}^{-}$. Tables 1 and 2 report summary statistics over our sample of each of these measures for 0DTEs and 1-22 DTEs, respectively. For 0DTEs, across all times of the day, the average $VRP_{t,T}$ is high and significantly positive, confirming the evidence from option returns that investors require substantial compensation to bear variance risk over the day. In fact, the annualized 0DTE $VRP_{t,T}$ varies from 1.54% to 2.95%, which is considerably larger than the 0.55% of 1DTEs or the 0.81% of 22DTEs. Interestingly, both $VRP_{t,T}$ components as implied by 0DTEs are significantly positive as well, where the compensation for upside risk is actually larger than the compensation for downside risk. This is in stark contrast to the evidence from longer horizons, where the average $VRP_{t,T}^{+}$ decreases with the maturity and becomes negative from 5DTE onwards, while

[23] Over the 1990-2019 sample, Beason and Schreindorfer (2022) show that at the one-month horizon 2/3 of the equity premium stem from returns between -30% and -10%, while states up to a monthly return of 5% account for around 120% of the equity premium, and higher returns contribute negatively to it. Over our more recent sample, returns between -30% and -10% retain their importance, but the absence of a pronounced U-shape makes positive returns contribute to the equity premium as well.

$VRP^-_{t,T}$ increases with the horizon and eventually dominates the total $VRP_{t,T}$.

Figure OA.3 plots, for 0DTEs across different times of the day, the time series of the (one-week moving average of the) $VRP_{t,T}$, $VRP^+_{t,T}$ and $VRP^-_{t,T}$. Up to 2022, the three measures are almost always positive, while afterwards negative values become more frequent. The largest spike in $VRP_{t,T}$ is associated with the Covid-19 crisis. During this period, the total variance risk premium reached extreme values such as 100%. Importantly, this spike is driven by both the upside risk premium ($VRP^+_{t,T}$) and the downside risk premium ($VRP^-_{t,T}$). This is in contrast to the patterns observed for 1-22 DTEs, as depicted in Figure OA.4, where the $VRP^+_{t,T}$ mostly contributes with negative spikes.

4.3 Intra-day return predictability

We further investigate whether ex-ante measures capturing information from 0DTE options are able to predict realized intra-day excess market returns from t to T with predictive regressions of the following form:

$$R_{t,T} - R_f = a + bX_t + \epsilon_{t,T}, \tag{17}$$

where X_t collects different predictors available in real time at t. We first focus on the variance risk premium and its components, given that these summarize the compensation investors require to bear variation risk in different regions of the market return space. Then, we analyze as predictors the risk-neutral variance, skewness and kurtosis as in Bakshi et al. (2003), the realized variance, and the SVIX of Martin (2017), which represents a lower bound for the equity premium under a negative correlation assumption.

Table 3 reports the results for univariate predictive regressions based on $VRP_{t,T}$, $VRP^+_{t,T}$ and $VRP^-_{t,T}$, and a multivariate regression including both $VRP^+_{t,T}$ and $VRP^-_{t,T}$. The total variance risk premium negatively predicts the intra-day equity premium, with statistical significance at most times of the day. This is at odds with the positive relation documented at monthly or longer horizons (Bollerslev et al., 2009). Using the two components of the $VRP_{t,T}$ in the predictive regressions sheds light on this finding. The $VRP^{+}_{t,T}$ is a strong predictor of market returns, with a negative coefficient that is statistically significant at nearly all times of the day. In contrast, there is a positive relation between $VRP^{-}_{t,T}$ and future returns, which is often insignificant and of weaker magnitude. That is, the results for $VRP_{t,T}$ are driven by $VRP^{+}_{t,T}$. The R^2's of the multivariate regressions are also much higher than those for the total $VRP_{t,T}$, which mainly comes from the predictive power of $VRP^{+}_{t,T}$, as can be seen from the univariate regressions.

The negative relation between $VRP^{+}_{t,T}$ and market returns from t to T is consistent with a U-shaped pricing kernel. As discussed in Section 2.3, the equity premium can be seen as the aggregate compensation required for holding assets paying R in each market return state, and zero otherwise. When marginal utility for positive market return states is high, such assets paying in positive return states are hedges (as they pay a high payoff when the pricing kernel is high). This is such that investors are willing to give up compensation to hold them, resulting in a smaller equity premium. As $VRP^{+}_{t,T}$ summarizes the compensation for positive return variation risk, this explains the negative relation with future returns. On the other hand, since the Arrow-Debreu-like assets paying R for negative return states behave as speculative assets (as they pay a low payoff when the pricing kernel is high), investors require compensation to hold them and they contribute positively to the equity premium. This explains the positive relation between $VRP^{-}_{t,T}$ and future market returns. The fact that the effect of $VRP^{+}_{t,T}$ is dominant over that of $VRP^{-}_{t,T}$ reflects the exceptional role that the U-shape plays in the intra-daily horizons. This, again, is in contrast to the one-month horizon or longer where the positive coefficient of $VRP^{-}_{t,T}$ is predominant and drives the positive relation between the total $VRP_{t,T}$ and the equity premium.

Table OA.1 contains the results for the univariate predictive regressions based on RV, risk-neutral skewness and kurtosis, and $SVIX$. As can be seen, none of these measures is able to predict the intra-day equity premium. That is, we find no evidence of an intra-day risk-return trade-off. In particular, the fact that the lower bound of Martin (2017), $SVIX$, does not predict future returns, could either mean that the bound is not tight at the intra-daily horizons we consider, or that the negative correlation assumption under which the bound is derived is not valid. More specifically, this assumption states that the covariance between $R_{t,T}$ and $m_{t,T}(R_{t,t}) \times R_{t,T}$ must be negative. While this condition is valid under most macro-finance models, it would be violated under a pricing kernel with pronounced nonmonotonicities. Given the extensive evidence from our analysis in favor of such nonmonotonicity over intra-daily horizons, this seems like a plausible explanation.

Table OA.2 further considers predictive regressions based on the variance risk premium measures including the risk-neutral moments as controls (results including RV instead of $SVIX$ are very similar). As can be observed, the inclusion of the controls can make the negative relation between the total variance risk premium and future market returns even stronger. Among the controls, $SVIX$ becomes marginally significant with a positive coefficient at 12:00, while the other variables have no predictive power. When we replace $VRP_{t,T}$ with its two components, we see that the R^2 increases substantially and $VRP^{+}_{t,T}$ is a stronger significant predictor of returns than $VRP^{-}_{t,T}$, where a higher value of the former leads to a lower equity premium. This provides additional robustness to the findings of this subsection.

4.4 Investors' risk preferences

The previous subsections provide indirect evidence that the pricing kernel as a function of market returns is nonmonotonic and high for positive market returns. In this subsection, we directly estimate the pricing kernel for each maturity and analyze its average shape over our sample. Figure 8 displays the results together with 90% confidence bands. For 0DTEs, regardless of the time of the day, there is a pronounced U-shaped pattern in the pricing kernel that is almost symmetric, such that marginal utility is high for both negative and positive returns, and often higher in the positive return region. This confirms the relative importance of compensation for upside risk in the 0DTE market.

Panel (b) of Figure 8 further reveals that the U-shaped pattern in the pricing kernel is concentrated at the shortest maturities below one week. For horizons between one and two weeks, nonmonotonicity is milder, and the pricing kernel is much higher for negative returns. Finally, for longer DTEs up to one month, the pricing kernel is mostly decreasing across returns, with mild nonmonotonicity in the ATM region, more closely resembling an S shape. Again, this is aligned with our previous evidence from option returns and risk premia, indicating that nonmonotonic patterns in the pricing kernel have mostly shifted to shorter maturities over recent years.

4.5 0DTE (mis)pricing according to risk-averse investors

So far, we have shown that 0DTE option prices can only be jointly reconciled with the physical distribution of market returns under a pricing kernel displaying pronounced nonmonotonicity. In this subsection, we address the problem from a different angle. For each option, we compute SSD bounds from the physical distribution consistent with all pricing kernels that are monotonically decreasing in market returns. In other words, we entertain the possibility that the option market is segmented and test whether, for each option, a risk-averse investor that is marginal in the market index and the risk-free rate would also be marginal in the option. As discussed in Section 2.5, a nonmonotonic pricing kernel projection does not necessarily imply that option prices violate SSD bounds.

Table 4 reports, for 0DTEs across different times of the day, the percentage over our sample of options on a given category that: satisfy the SSD bounds; violate the upper bound; or violate the lower bound. Patterns are similar across the day. Strikingly, only around 25% (35%) of the call (put) prices are consistent with monotonically decreasing pricing kernels. This is mainly driven by the ATM category, where only around 6% of the prices satisfy the SSD bounds. In particular, we observe mainly upper bound violations, meaning that ATM option prices are usually too high, in the sense that any risk-averse investor would improve expected utility by selling ATM options. On the other hand, OTM calls and puts rarely violate the upper bound, while their prices are below the lower bound reasonably often, i.e., they are generally too cheap from the perspective of these investors.[24] ITM options frequently violate both the upper and lower bound, which can be due to the fact that they are less liquid and may present unreliable prices. Table 5 provides the analogous evidence for options from 1 to 22 DTE. As can be seen, violations of the SSD bounds decrease monotonically with the maturity, where there is essentially no mispricing at the one-month horizon. In other words, while 22DTE option prices can be reconciled with the physical distribution of market returns under risk-averse preferences, the underlying and option markets are much less integrated over ultra-short horizons.

To assess the economic significance of the mispricing we identify for 0DTEs, we build a trading strategy that exploits the SSD bounds violations. The strategy focuses on the ATM option and is defined as follows. If the option is overpriced (underpriced) with respect to the underlying asset according to risk-averse investors – i.e., if the option represents an upper (lower) bound violation – we write (purchase) the option and buy (sell) delta shares of the underlying. If, instead, the option price is inside the SSD bounds, we go long on the risk-free rate. As a benchmark, we consider the strategy that always sells the ATM delta-hedged option, which amounts to exploiting the variance risk

[24]There is no inconsistency between options being "cheap" according to risk-averse investors and "expensive" in terms of high IVs as each criteria benchmark prices relative to those implied by different distributions: the former with respect to the physical distribution adjusted by monotonically decreasing pricing kernels and the latter to a log-normal distribution. Options can also be "expensive" in terms of low average returns but "cheap" according to risk-averse investors if the SSD lower bound price is already enough to generate such low returns.

premium. The SSD violation strategy would be equivalent to this benchmark if the ATM option always violated the upper bound.

Table 6 reports the Sharpe ratio of the SSD violation strategy and the benchmark for different times of the day, before and after transaction costs. We focus on the ATM call, as results for the ATM put are very similar. To incorporate transaction costs, whenever we buy (sell) the option, we consider the ask (bid) price instead of the bid-ask midpoint, that is, we consider the worst case scenario for the strategy. As can be seen, the SSD violation strategy is highly profitable, yielding Sharpe ratios in the range of 0.1 to 0.2 for very short-term horizons. These Sharpe ratios are an order of magnitude larger than those obtained from selling the ATM delta-hedged call. In particular, transaction costs have a small impact on the performance of the SSD strategy, while the benchmark produces mostly negative Sharpe ratios net of costs. The profitability associated with the SSD violation strategy reinforces our finding that 0DTE options are mispriced. In fact, if our results were driven by misspecification of the estimated physical distribution, it is very unlikely that exploiting the violations would lead to such economic gains.

Figure 9 further plots the cumulative returns of the strategies at two different times of the day, before and after transaction costs. Returns are adjusted to have unit standard deviation to reflect risk-adjusted performance. The SSD violation strategy has a remarkably stable performance up to 2022, while the benchmark is more erratic and experiences long periods with decreasing cumulative returns. This highlights the economic significance of the lower bound violations, which signal when the strategy should go long in the ATM delta-hedged call instead of going short. After 2022, the performance of the strategy mostly stagnates, suggesting growing market efficiency and stronger integration between the underlying and 0DTE markets over recent years.

To shed further light on the economic significance of the mispricing we document, we compute Sharpe ratios after transaction costs conditioned to different variables being above the median (high) or below the median (low) in our sample.[25] Table 7 reports the results. The Sharpe ratio of the SSD violation strategy is higher when the 0DTE volume, realized variance and attention to the 0DTE option market (measured with Google trends) are low. In other words, the mispricing is more pronounced, in economic terms, when liquidity is low, uncertainty is low and agents are not paying attention to 0DTEs. On the other hand, conditioning on the VRP has only a small effect on the Sharpe ratio of the violation strategy, reinforcing that the strategy is not simply exploiting the variance risk premium. In fact, its risk-adjusted profitability is slightly larger when the VRP is low. Overall, these results are consistent with the idea that after the daily availability of 0DTEs and the associated increase in liquidity and attention to these options, the profitability of the SSD violation strategy is greatly reduced.

5 Robustness checks

In this section, we provide robustness checks for our main results. More specifically, we investigate how our findings are affected if we consider the sample before and after the daily availability of 0DTE options, and if we remove days with FOMC announcements. Tables and figures supporting this analysis are collected in the Online Appendix.

5.1 Before and after 2022

As previously mentioned, since the introduction of Thursday expirations in May 11 2022, 0DTE options on the S&P 500 index are available on a daily basis. This comes hand in hand with the largest increase in 0DTE trading volume in recent years, as seen in Figure 1. In this subsection, we investigate how our results are affected by splitting the sample before and after May 11 2022.

[25]Figure OA.5 depicts the time-series of these variables together with their median.

Table OA.3 reports the average 0DTE VRP, VRP^{+} and VRP^{-} on the two subsamples. The average variance risk premium is significantly positive in both cases, albeit larger before May 11 2022. Upon inspection of Panels B and C, we can see that this is mainly because the compensation for downside risk is larger before May 11 2022. In fact, after this date, statistical significance of the average VRP^{-} is reduced. In contrast, the compensation for upside risk is similar for both subsamples. Table OA.4 contains the results for 1-22 DTEs, which are also similar to those based on the whole sample, where the VRP^{+} decreases from shorter to longer maturities, becoming negative or insignificant, while the VRP^{+} increases with the horizon.

Table OA.5 contains the intra-day market return predictability exercise with variance risk premium variables. Focusing first on the VRP, it negatively predicts market returns for both subsamples, with statistical significance for most cases. When decomposing the VRP into its two components, we can see that the VRP^{+} negatively predicts the equity premium both before and after May 11 2022, also with statistical significance for most times of the day. In contrast, VRP^{-} is mostly insignificant before May 11 2022, while it significantly predicts market returns with a negative relation afterwards.

Table OA.6 further reports the option price bounds results for 0DTEs before and after May 11 2022. The proportion of calls inside the bounds increases to around 30% with the daily availability of 0DTEs. This is mainly because bound violations for ITM calls decrease. Interestingly, lower bound violations for ATM calls become rare, while upper bound violations dominate. This indicates that ATM calls are most of the time expensive in the most recent subsample according to risk-averse investors, which might explain the performance deterioration of the SSD strategy as it will almost always sell the ATM call delta-hedged. Results for puts are similar, with the exception that violations for OTM puts increase, which is mainly due to lower bound violations. That is, OTM puts are in general too cheap according to the stochastic dominance criterion. For 1-22 DTEs in

Table OA.7, there are more violations of the bounds after May 11 2022, but the relative patterns across maturities are similar.

Finally, Figures OA.6 and OA.7 depict the average pricing kernel before and after May 11 2022, respectively. Observed patterns are very similar for short horizons across the subsamples, while there is stronger evidence of nonmonotonicity for the pricing kernel implied by options with one week to one month maturities after May 11 2022.

5.2 FOMC announcements

0DTEs allow investors to hedge and make leveraged bets on specific intra-daily market movements and resolution of uncertainty, which is especially relevant for days with events that can affect financial markets. Announcements from Federal Open Market Committee (FOMC) meetings are arguably the most important kind of events happening during regular trading hours (around 14:00) that are relevant for 0DTEs. During our sample, there are 68 FOMC announcement days coinciding with dates for which 0DTEs were traded. Rather than analyzing effects in such a relatively small sample,[26] we investigate how our results are affected by excluding FOMC announcement dates from our sample.

Table OA.8 reports the average VRP, VRP^+ and VRP^- over our sample after removing days with FOMC announcements. The only change with respect to Table 1 is that the variance risk premium and its components are on average smaller once FOMC days are excluded. However, they are still economically large and statistically significant, and the VRP^+ continues to dominate the VRP^-. That is, our conclusions regarding the compensation investors require to bear variance risk over the day are not affected by FOMC announcements.

[26] For instance, Figure OA.8 plots average returns of ATM delta-hedged calls and straddles on FOMC announcement days. Before the announcement, average returns are mostly negative, while around the announcement and its resolution of uncertainty, average returns become positive, such that investors would not be willing to pay for protection against variance risk anymore. However, average returns are not statistically significant due to the small sample, making it difficult to draw conclusions.

Table OA.9 contains the market return predictability exercise with variance risk premium variables when removing FOMC announcement days. Focusing first on the VRP, it continues to negatively predict market returns, but with smaller statistical significance. The VRP^+ also has its significance somewhat reduced compared to the total sample, but it is still significant for most times of the day in the regression including VRP^-. This indicates that FOMC announcement days are relevant for the predictive relation between compensation for variation risk and market returns, but do not solely account for this relation.

Tables OA.10 and OA.11 report the option price bounds results and the Sharpe ratios for the SSD violation strategy for days without FOMC announcements. Both tables show that these results are essentially unaffected by removing FOMC days. In other words, the stochastic dominance violations and the profitability associated with these violations are not explained by FOMC announcements. Finally, Figure OA.9 depicts the average pricing kernel over our sample without FOMC days, which is again largely the same as for the total sample.

6 Conclusion

We explore the asset pricing implications of the new 0DTE option market, which today accounts for more than half of total S&P 500 option volume. These options contain new, valuable information about investors' risk preferences and risk premia over the intra-daily horizons for which the options expire. We extract this information from different perspectives to document a number of new asset pricing stylized facts, contrasting them with evidence from longer horizons.

A distinctive feature of the 0DTE market is that investors mainly require compensation for positive market returns, rather than negative returns. This is reflected in low average returns of call options and a high variance risk premium that is largely driven by compensation for upside risk. The variance risk premium also negatively predicts market returns over the day, which is mainly driven by the negative relation between future returns and the compensation for upside risk. In contrast, for longer horizons up to a month, the variance risk premium is smaller, dominated by compensation for downside risk, and positively predicts market returns. Moreover, most 0DTEs appear mispriced from the perspective of risk-averse investors. A trading strategy exploting this mispricing is highly profitable before 2022, but stagnates after the daily availability of 0DTEs, consistent with growing integration between the 0DTE and underlying markets.

Our empirical results are all consistent with a strong U-shape in the intra-day pricing kernel as a function of market returns, which we confirm with direct estimates. While there is a large literature documenting pricing kernel nonmonotonicity at the one-month horizon, we show that over recent years these nonmonotonic patterns have shifted towards ultra-short maturities, and especially the intra-daily horizons of 0DTE options.

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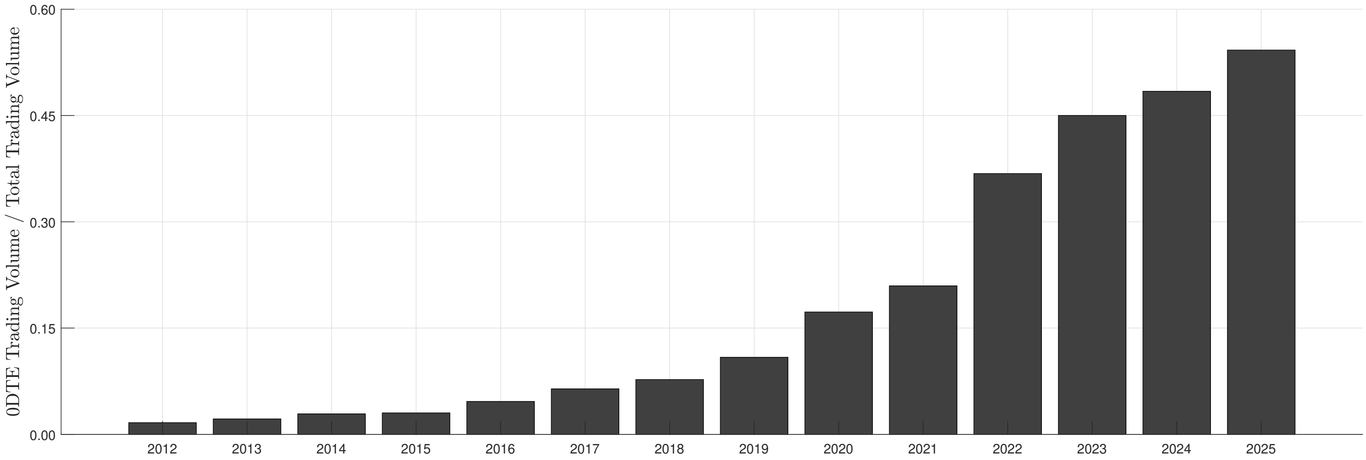
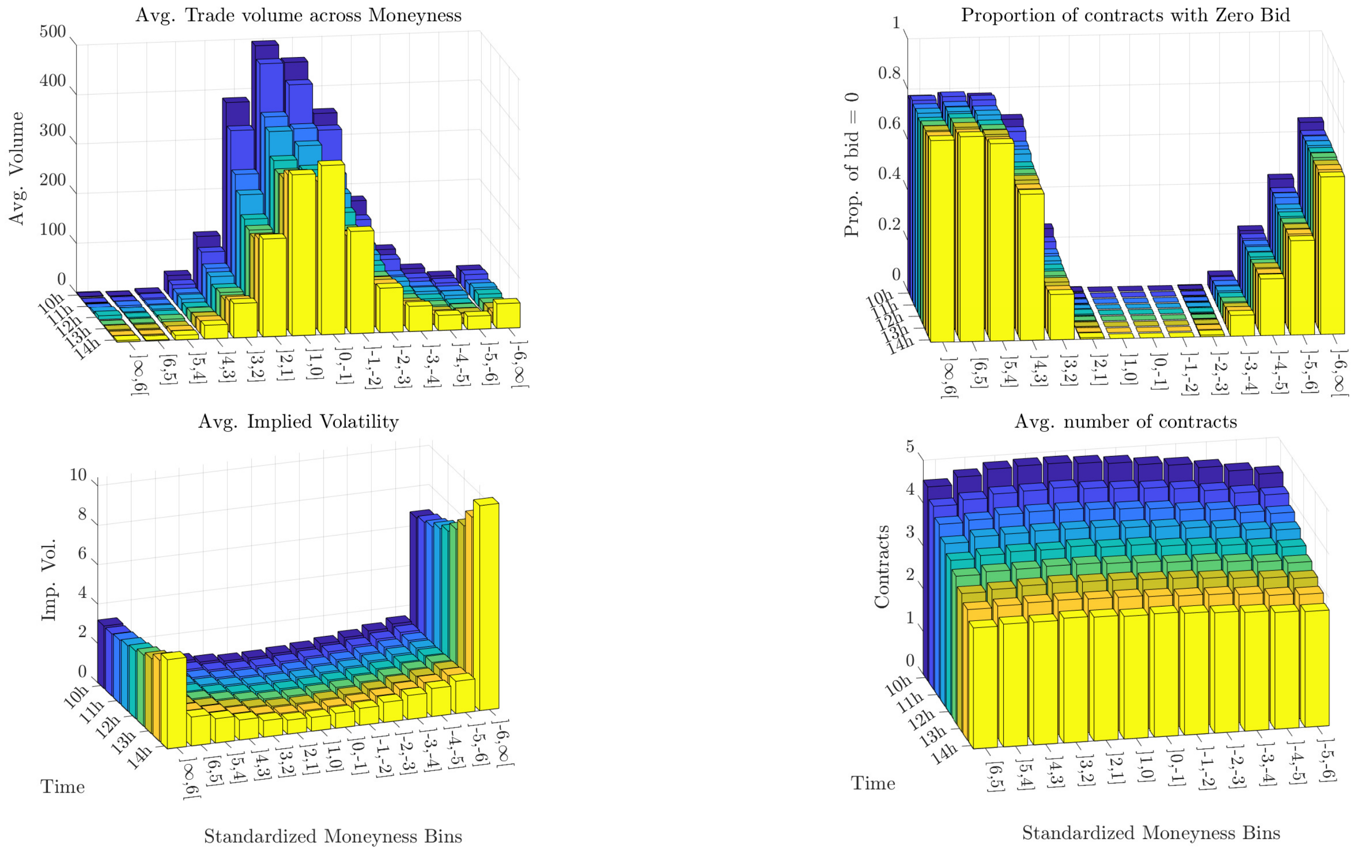
A Figures and tables

Figure 1: Yearly fraction of trading volume in 0DTE options



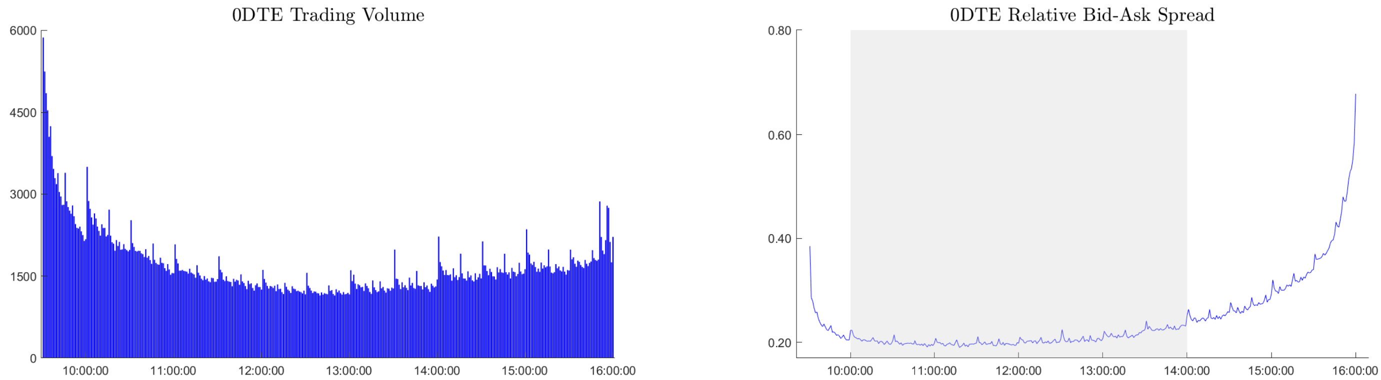
Note: The figure depicts the yearly fraction of trading volume in 0DTE S&P 500 options relative to the entire S&P 500 option market. The sample ranges from January 6 2012 to March 18 2025.

Figure 2: Descriptive statistics of raw 0DTE option data



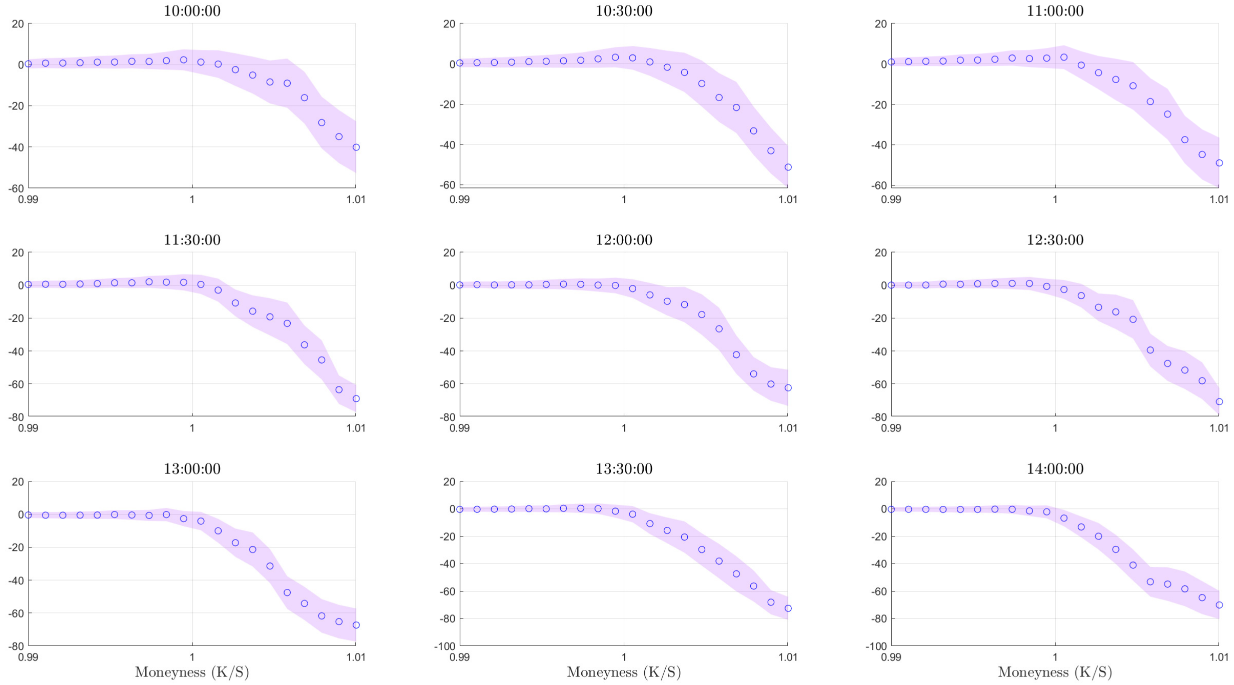
Note: The figure plots, in four subplots, for different times of the day and different standardized log-moneyness bins, the average trading volume, proportion of contracts with zero bid, average implied volatility and average number of strikes. The sample ranges from January 6 2012 to March 18 2025.

Figure 3: Trading volume and relative bid-ask spread of 0DTE options over the day

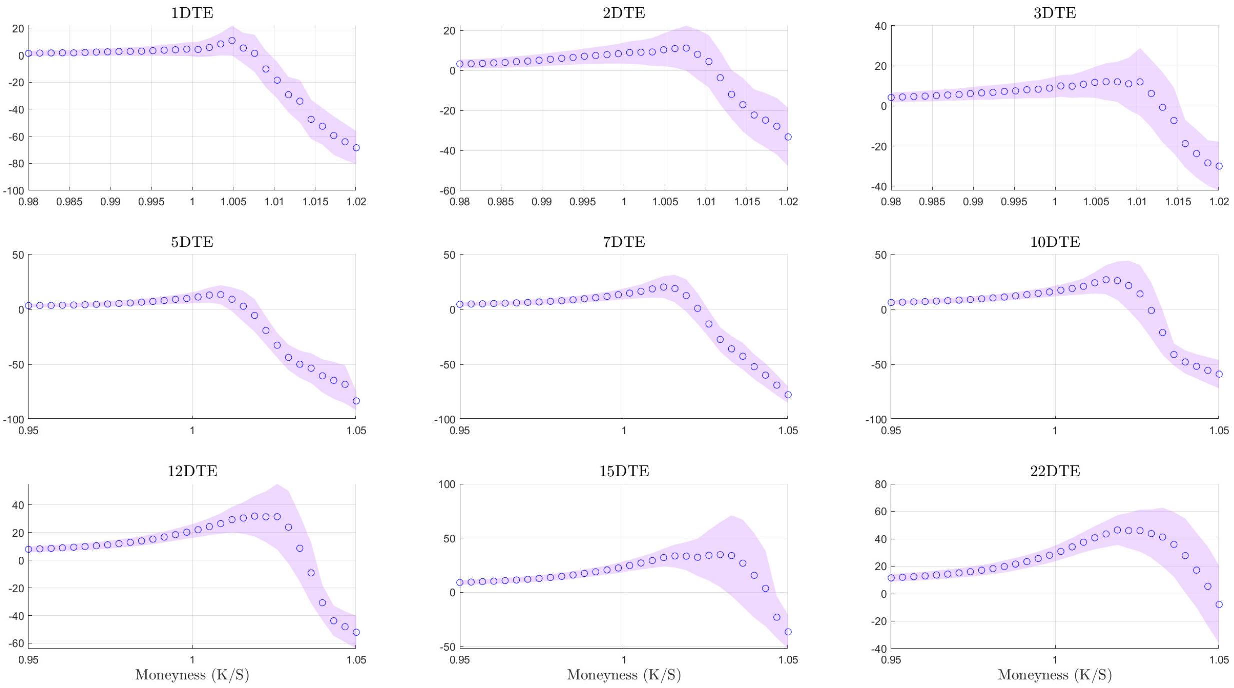


Note: The left plot of this figure depicts the time series average of the trading volume in terms of number of contracts of 0DTE S&P 500 options over the day. The right plot depicts the time series average of the average relative bid-ask spread across all 0DTE options over the day, where the relative spread is computed as $(Ask - Bid)/MidQuote$. The sample ranges from January 6 2012 to March 18 2025.

Figure 4: Average call returns across strikes



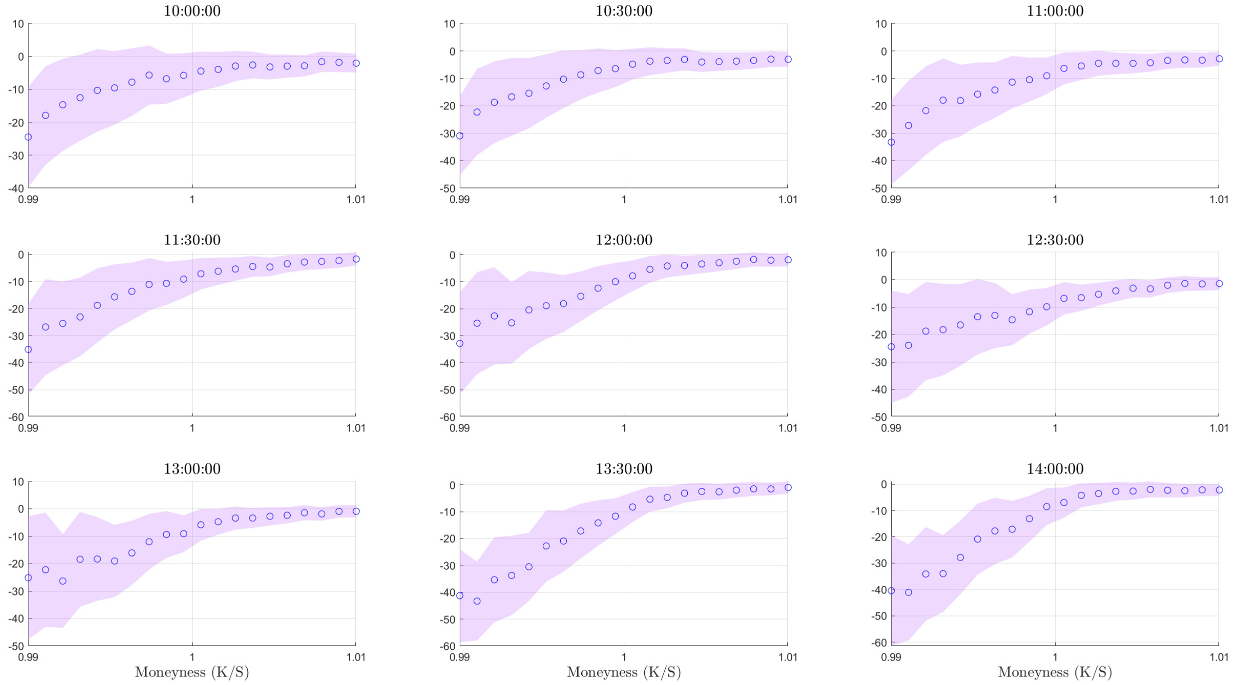
(a) 0DTEs



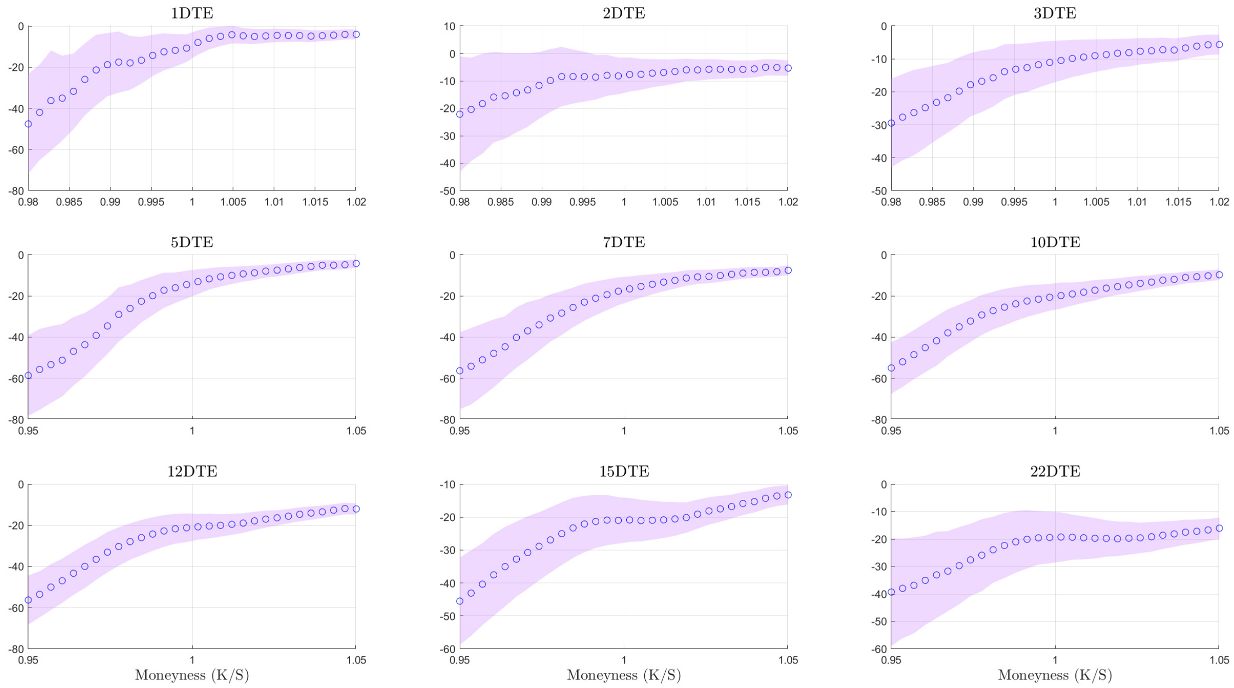
(b) 1-22 DTEs

Note: The figure shows the average returns (in %) of 0DTE (Panel a) and 1-22 DTE (Panel b) call options across different strikes with 90% confidence bands. For a given moneyness, 0DTE option returns over the time-series are winsorized in the right-tail at 0.5%, i.e., returns above the 99.5% quantile are set to that quantile. Confidence bands are based on 2,500 bootstrap replications. The sample ranges from January 6 2012 to March 18 2025.

Figure 5: Average put returns across strikes



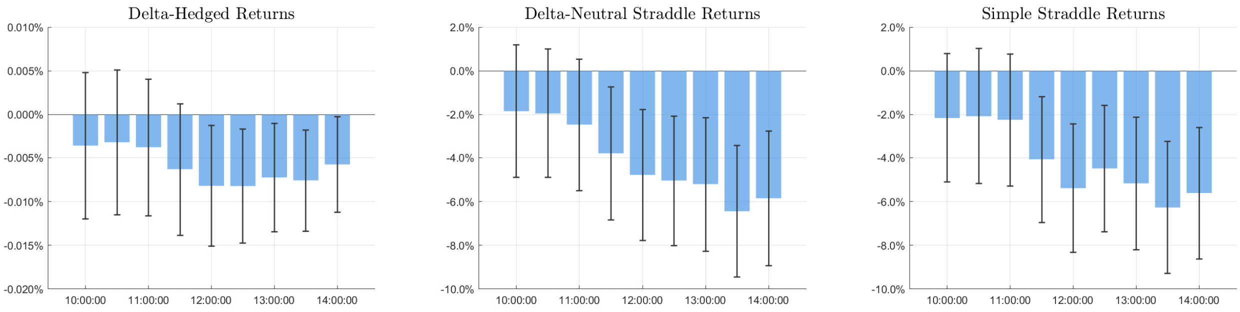
(a) 0DTEs



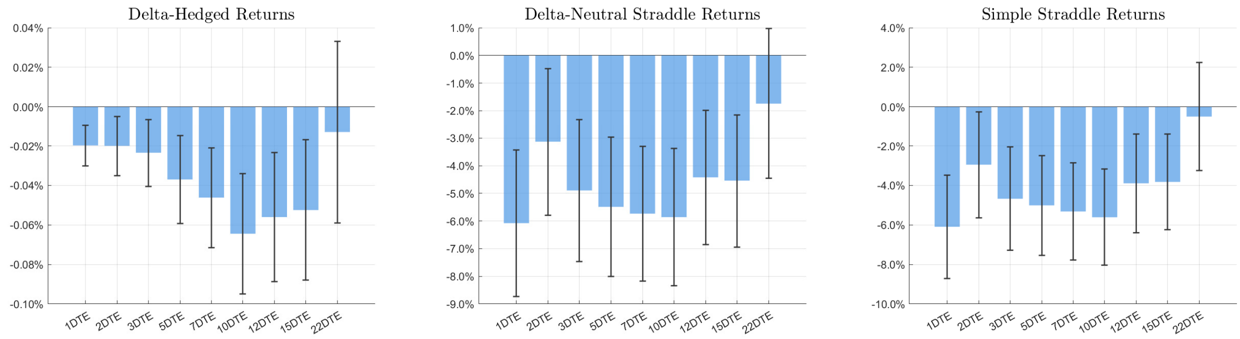
(b) 1-22 DTEs

Note: The figure shows the average returns (in %) of 0DTE (Panel a) and 1-22 DTE (Panel b) put options across different strikes with 90% confidence bands. For a given moneyness, 0DTE option returns over the time-series are winsorized in the right-tail at 0.5%, i.e., returns above the 99.5% quantile are set to that quantile. Confidence bands are based on 2,500 bootstrap replications. The sample ranges from January 6 2012 to March 18 2025.

Figure 6: Average returns of option strategies



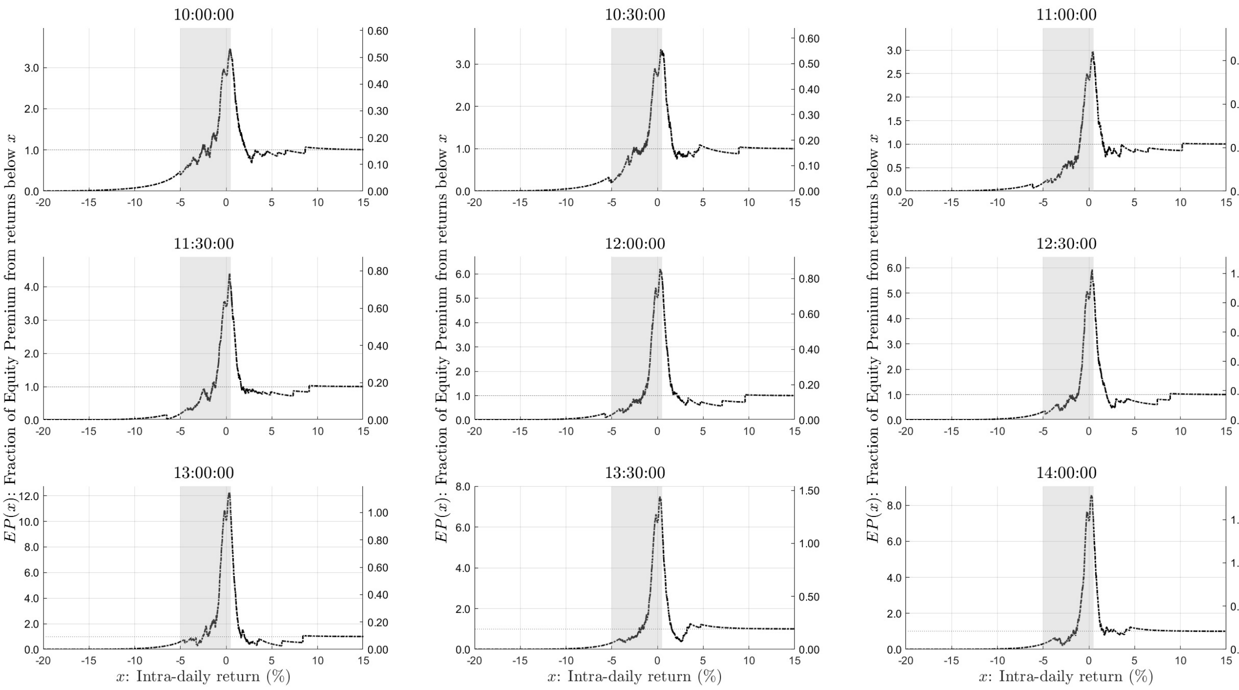
(a) 0DTEs



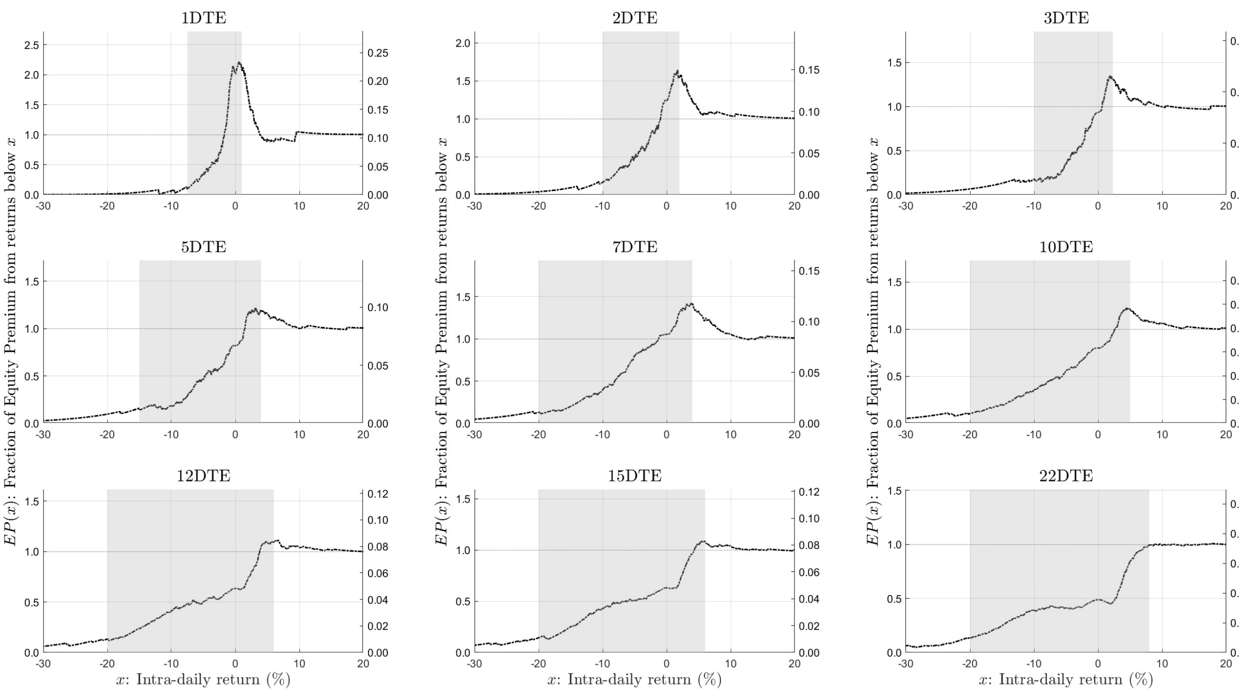
(b) 1-22 DTEs

Note: The figure shows the average returns (in %) of 0DTE (Panel a) and 1-22 DTE (Panel b) option strategies with 90% confidence bands. For 0DTEs (1-22 DTEs), returns over the time-series are winsorized in the right-tail at 1% (5%). Confidence bands are based on 2,500 bootstrap replications. The sample ranges from January 6 2012 to March 18 2025.

Figure 7: Equity premium decomposition



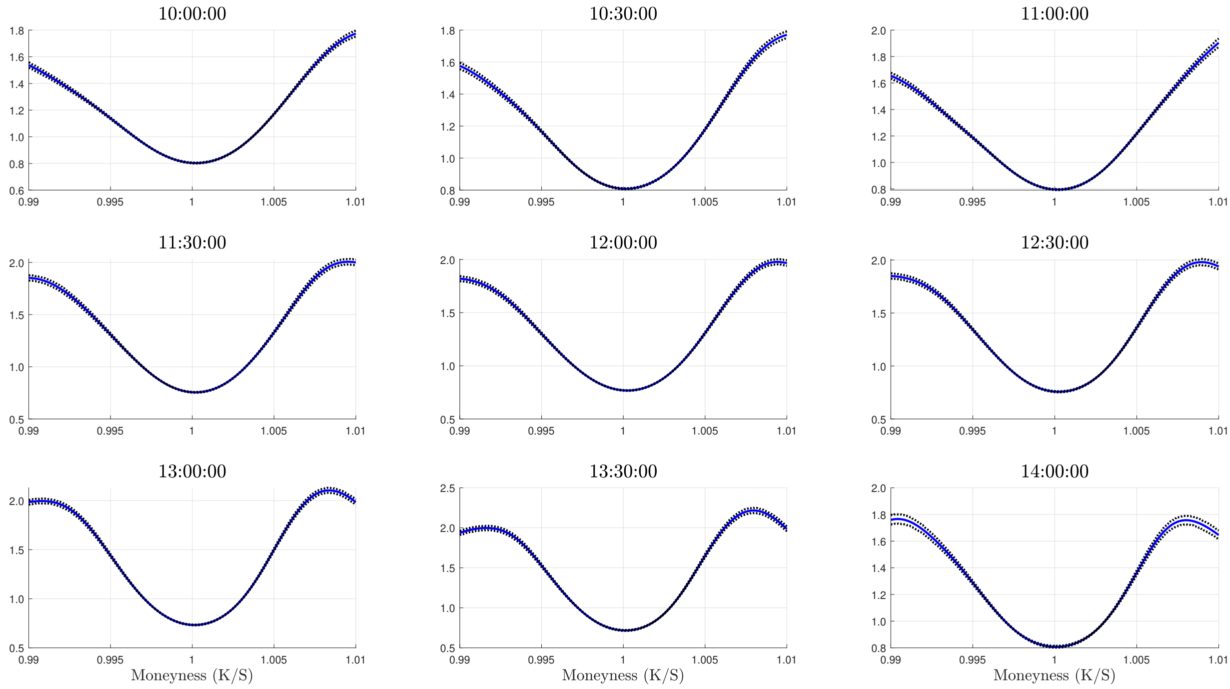
(a) 0DTEs



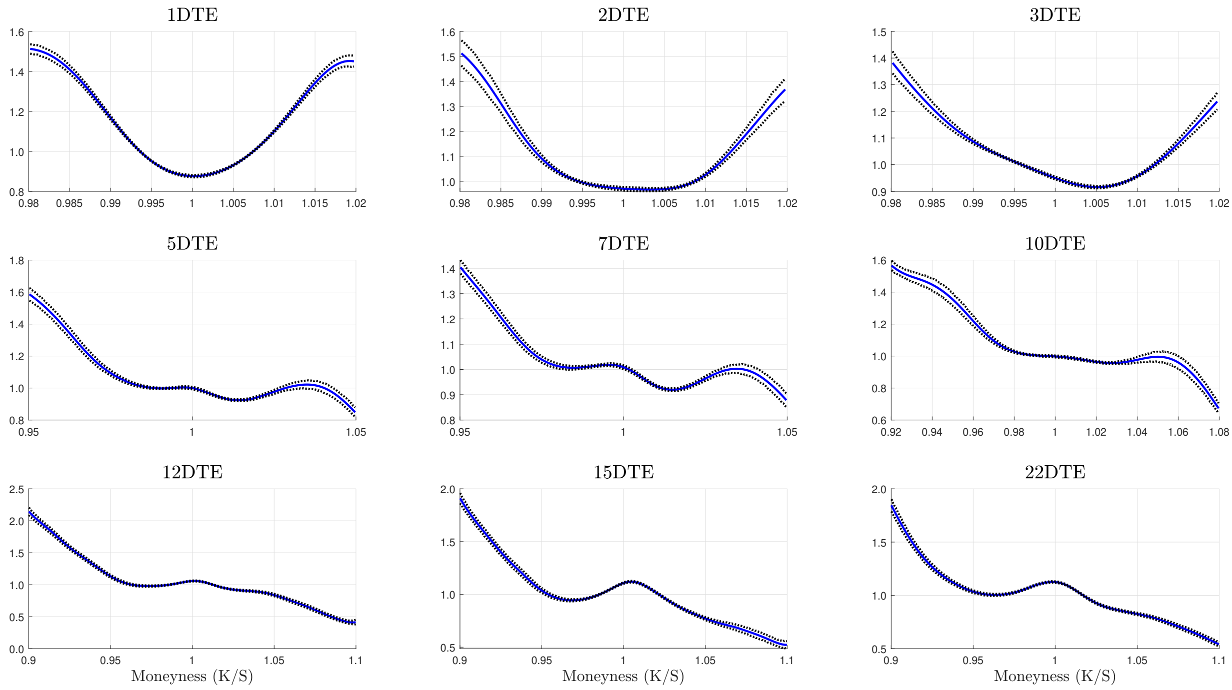
(b) 1-22 DTEs

Note: The figure plots the equity premium decomposition implied by 0DTEs (Panel a) and 1-22 DTEs (Panel b). The left vertical axis displays the fraction of the equity premium stemming from market returns below x, while the right vertical axis displays the total annualized equity premium that would be implied from market returns up to x. The sample ranges from January 6 2012 to March 18 2025.

Figure 8: Average pricing kernels



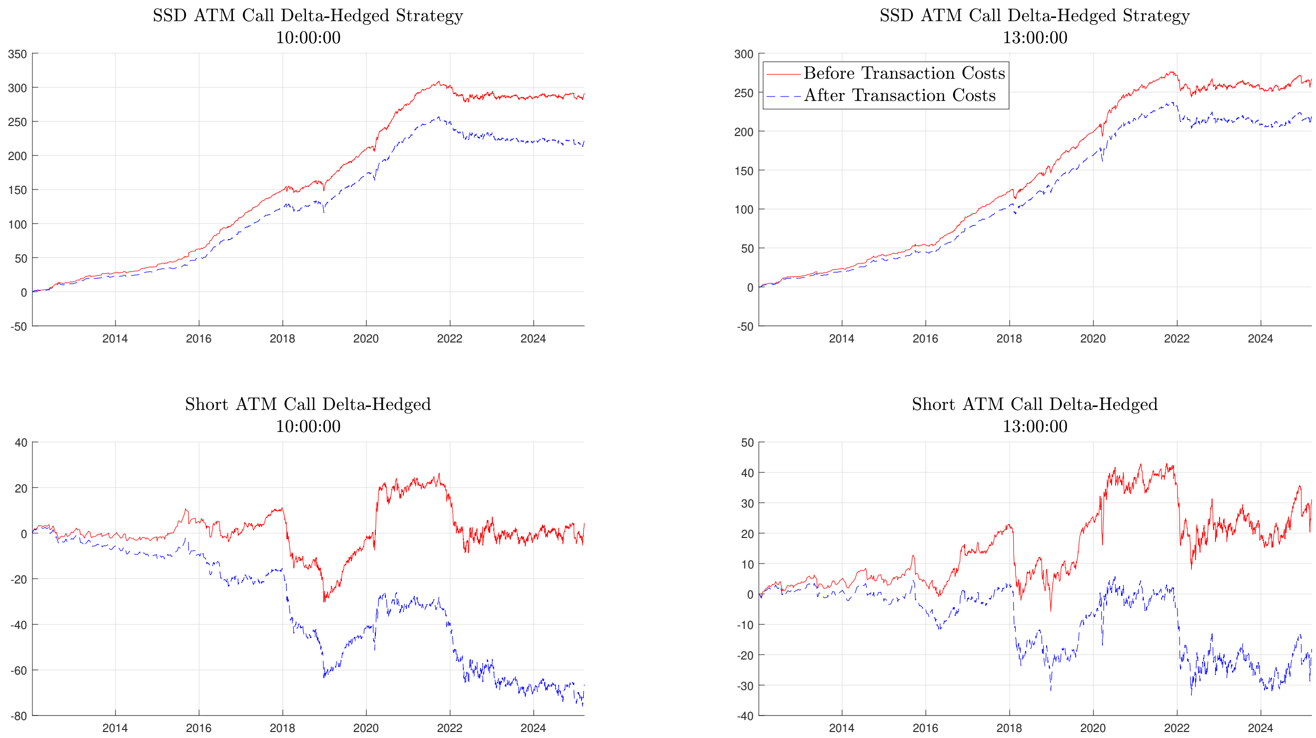
(a) 0DTEs



(b) 1-22 DTEs

Note: The figure plots the average of the pricing kernel, as a function of market returns, implied by 0DTEs (Panel a) and 1-22 DTEs (Panel b) with 90% confidence bands. Confidence bands are based on 1,000 bootstrap replications. The sample ranges from January 6 2012 to March 18 2025.

Figure 9: Cumulative returns of SSD violation strategy



Note: The figure plots, for two different times of the day, the cumulative returns of the SSD violation strategy based on the ATM call (in the upper panels) and the benchmark strategy writing the ATM call delta-hedged (in the lower panels). To incorporate transaction costs, whenever we buy (sell) the option, we consider the ask (bid) price instead of the bid-ask midpoint, that is, we consider the worst case scenario for the strategy. Returns are adjusted to have standard deviation of one. The sample ranges from January 6 2012 to March 18 2025.

Table 1: Intra-day variance risk premium

	10:00:00	10:30:00	11:00:00	11:30:00	12:00:00	12:30:00	13:00:00	13:30:00	14:00:00
Panel A: VRP									
Mean	1.804	1.562	1.540	1.717	1.806	2.205	1.981	2.460	2.956
St. Dev.	9.124	7.633	8.051	9.060	8.669	13.788	10.020	12.266	14.414
25th Percentile	0.182	0.152	0.209	0.212	0.233	0.281	0.325	0.341	0.375
75th Percentile	1.994	1.915	1.973	2.126	2.271	2.332	2.480	2.850	3.158
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: VRP^+									
Mean	0.957	0.935	0.956	1.137	1.131	1.533	1.402	1.650	1.971
St. Dev.	3.708	3.518	3.532	5.559	4.070	9.915	4.956	6.102	7.364
25th Percentile	0.261	0.303	0.315	0.349	0.378	0.417	0.512	0.600	0.687
75th Percentile	1.231	1.256	1.297	1.430	1.532	1.614	1.789	2.009	2.304
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: VRP^-									
Mean	0.847	0.627	0.584	0.580	0.675	0.672	0.579	0.810	0.985
St. Dev.	5.869	4.647	5.012	4.359	4.953	5.523	5.379	6.407	7.452
25th Percentile	−0.115	−0.147	−0.160	−0.169	−0.212	−0.232	−0.230	−0.279	−0.359
75th Percentile	0.795	0.715	0.715	0.751	0.757	0.749	0.781	0.882	0.938
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table reports, for each time of the day for the 0DTEs, summary statistics of the $VRP_{t,T}$, $VRP^+_{t,T}$ and $VRP^-_{t,T}$ over our sample. The variance risk premium measures are annualized and expressed in percentage points. The p-values for the test with null hypothesis that the mean is smaller than or equal to zero, against the alternative that the mean is positive, are implemented using bootstrapped standard errors with 2,500 replications. The sample ranges from January 6 2012 to March 18 2025.

Table 2: Variance risk premium

	1DTE	2DTE	3DTE	5DTE	7DTE	10DTE	12DTE	15DTE	22DTE
Panel A: VRP									
Mean	0.558	0.671	0.477	0.489	0.545	0.596	0.663	0.701	0.812
St. Dev.	9.123	5.714	5.208	4.494	4.996	4.713	4.804	4.513	3.502
25th Percentile	0.003	0.101	0.085	0.040	0.134	0.207	0.277	0.323	0.391
75th Percentile	1.413	1.361	1.271	1.205	1.276	1.374	1.376	1.501	1.477
p-value	0.011	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: VRP^{+}									
Mean	0.296	0.133	0.010	−0.122	−0.202	−0.259	−0.267	−0.304	−0.217
St. Dev.	2.521	2.127	1.979	1.728	1.869	1.926	1.855	1.928	1.472
25th Percentile	0.013	−0.040	−0.093	−0.168	−0.196	−0.275	−0.293	−0.321	−0.288
75th Percentile	0.768	0.688	0.555	0.346	0.295	0.250	0.222	0.212	0.190
p-value	0.000	0.009	0.831	0.002	0.000	0.000	0.000	0.000	0.000
Panel C: VRP^{-}									
Mean	0.262	0.539	0.466	0.611	0.747	0.855	0.930	1.004	1.029
St. Dev.	8.515	4.808	4.008	3.381	3.638	3.181	3.336	2.913	2.240
25th Percentile	0.074	0.135	0.158	0.184	0.280	0.365	0.415	0.477	0.524
75th Percentile	0.834	0.825	0.880	0.959	1.119	1.251	1.323	1.460	1.351
p-value	0.188	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table reports, for each maturity, summary statistics of the $VRP_{t,T}$, $VRP^{+}_{t,T}$ and $VRP^{-}_{t,T}$ over our sample. The variance risk premium measures are annualized and expressed in percentage points. The p-values for the test with null hypothesis that the mean equals zero, against the alternative that the mean is different from zero, are implemented using bootstrapped standard errors with 2,500 replications. The sample ranges from January 6 2012 to March 18 2025.

Table 3: Predicting excess market returns with variance risk premium

	10:00:00				10:30:00				11:00:00			
VRP	$-0.049^{\star}$				-0.049				$-0.068^{\star\star\star}$			
t-stat	-1.723				-1.535				-2.721			
VRP^{+}		$-0.091^{\star\star\star}$		$-0.218^{\star\star\star}$		$-0.077^{\star\star}$		$-0.134^{\star\star}$		$-0.107^{\star\star\star}$		$-0.199^{\star\star\star}$
t-stat		-2.948		-4.105		-2.322		-1.970		-3.365		-3.011
VRP^{-}			-0.018	$0.158^{\star\star\star}$			-0.022	0.078			-0.034	$0.119^{\star\star}$
t-stat			-0.539	3.457			-0.727	0.997			-1.441	2.325
$R^2(\%)$	0.407	1.436	0.055	2.950	0.461	1.133	0.095	1.652	0.955	2.361	0.237	3.540
	11:30:00				12:00:00				12:30:00			
VRP	$-0.056^{\star\star}$				$-0.095^{\star\star\star}$				$-0.037^{\star}$			
t-stat	-2.156				-3.823				-1.830			
VRP^{+}		$-0.076^{\star}$		$-0.111^{\star}$		$-0.103^{\star\star\star}$		$-0.119^{\star}$		-0.039		-0.038
t-stat		-1.916		-1.696		-3.306		-1.837		-1.287		-0.811
VRP^{-}			-0.020	0.053			$-0.082^{\star\star\star}$	0.019			-0.023	-0.001
t-stat			-0.859	1.404			-3.872	0.377			-0.886	-0.026
$R^2(\%)$	0.729	1.318	0.096	1.684	2.366	2.783	1.745	2.810	0.389	0.430	0.144	0.430
	13:00:00				13:30:00				14:00:00			
VRP	$-0.090^{\star\star\star}$				$-0.049^{\star}$				$-0.060^{\star\star\star}$			
t-stat	-4.626				-1.918				-2.386			
VRP^{+}		$-0.109^{\star\star\star}$		$-0.222^{\star\star\star}$		$-0.062^{\star\star\star}$		$-0.203^{\star\star\star}$		$-0.068^{\star\star\star}$		$-0.117^{\star\star\star}$
t-stat		-3.892		-3.308		-2.625		-3.419		-2.809		-2.784
VRP^{-}			$-0.067^{\star\star\star}$	$0.128^{\star\star}$			-0.034	$0.153^{\star\star\star}$			$-0.049^{\star}$	0.055
t-stat			-3.904	2.509			-1.267	2.687			-1.870	1.385
$R^2(\%)$	2.622	3.863	1.453	5.075	0.836	1.345	0.418	2.562	1.430	1.816	0.963	2.058

Note: The table reports, for each time of the day, the results from different predictive regressions over our sample using $VRP_{t,T}$, $VRP^{+}_{t,T}$ and $VRP^{-}_{t,T}$ to predict the excess market return from t to T. Regressors are standardized to have mean zero and unit variance. We compute the t-statistics using Newey-West robust standard errors with a lag length equal to 5. We denote with *, **, and *** significance at the 10%, 5% and 1% level, respectively. The sample ranges from January 6 2012 to March 18 2025.

Table 4: Option price bounds for 0DTE options

		10:00:00	10:30:00	11:00:00	11:30:00	12:00:00	12:30:00	13:00:00	13:30:00	14:00:00
Panel A: Calls										
All Calls	In	23.366	24.278	25.273	27.003	25.397	29.473	20.269	16.196	22.209
	Upper	41.114	39.939	39.905	39.156	39.092	36.901	43.417	45.598	43.744
	Lower	35.520	35.782	34.822	33.842	35.510	33.626	36.314	38.206	34.047
OTM	In	30.736	33.682	35.603	38.388	36.352	41.287	29.528	20.272	29.844
	Upper	5.056	6.847	8.178	7.544	8.178	6.638	7.296	6.919	7.889
	Lower	64.209	59.471	56.218	54.068	55.469	52.075	63.176	72.809	62.267
ATM	In	7.294	6.725	4.976	5.627	5.162	6.320	3.776	2.809	3.729
	Upper	78.711	78.656	80.646	80.753	81.847	82.105	84.827	83.856	82.801
	Lower	13.995	14.618	14.378	13.620	12.991	11.575	11.396	13.335	13.469
ITM	In	28.088	28.471	30.308	32.085	30.022	35.046	23.823	20.661	27.459
	Upper	38.961	36.241	34.723	33.493	32.753	29.181	40.103	44.972	41.430
	Lower	32.951	35.288	34.969	34.422	37.225	35.773	36.074	34.367	31.111
Panel B: Puts										
All Puts	In	32.191	33.598	33.584	36.628	34.812	39.141	31.215	28.060	34.778
	Upper	32.038	32.933	34.177	33.176	33.960	31.181	35.593	38.205	34.325
	Lower	35.772	33.469	32.239	30.196	31.228	29.679	33.192	33.736	30.897
OTM	In	47.650	49.380	50.013	55.421	53.079	59.322	48.631	45.194	54.576
	Upper	10.844	12.403	13.687	11.646	12.396	8.816	16.278	21.191	14.021
	Lower	41.507	38.217	36.300	32.932	34.525	31.862	35.091	33.614	31.403
ATM	In	8.078	7.226	5.474	5.854	5.336	6.788	3.845	2.900	4.092
	Upper	77.783	80.659	83.165	83.591	85.247	83.536	85.749	85.277	84.659
	Lower	14.139	12.116	11.360	10.555	9.417	9.676	10.406	11.823	11.249
ITM	In	23.405	26.986	27.823	27.663	25.874	28.517	21.116	14.963	20.805
	Upper	25.338	22.361	22.354	22.688	22.596	20.821	19.925	20.323	21.510
	Lower	51.258	50.652	49.823	49.649	51.530	50.662	58.959	64.714	57.686

Note: The table reports, for each time of the day and for each class of options, the percentage of options over our sample for which 0DTE prices fall within the SSD bounds (In), above the SSD upper bound (Upper) and below the SSD lower bound (Lower). The OTM put (ITM call), ATM and ITM put (OTM call) categories are defined as standardized log-moneyness below -1, between -1 and 1, and above 1, respectively. The sample ranges from January 6 2012 to March 18 2025.

Table 5: Option price bounds for 1-22 DTE options

		1DTE	2DTE	3DTE	5DTE	7DTE	10DTE	12DTE	15DTE	22DTE
Panel A: Calls										
All Calls	In	48.672	62.477	70.391	76.507	83.147	87.261	90.343	93.434	97.136
	Upper	33.836	23.013	17.259	13.276	10.021	7.489	5.395	3.406	1.001
	Lower	17.492	14.510	12.350	10.217	6.832	5.250	4.262	3.161	1.863
OTM	In	62.431	74.558	84.242	90.407	93.275	94.827	96.245	96.799	98.632
	Upper	3.892	2.494	2.260	1.814	1.414	1.766	1.359	1.695	0.695
	Lower	33.677	22.948	13.498	7.779	5.311	3.407	2.397	1.507	0.674
ATM	In	16.225	32.628	45.543	58.466	69.992	79.700	85.703	91.950	97.501
	Upper	82.172	65.672	52.857	40.098	29.041	19.562	13.639	7.612	2.216
	Lower	1.603	1.702	1.600	1.436	0.967	0.738	0.658	0.438	0.284
ITM	In	58.968	73.140	78.137	81.516	87.561	89.988	91.812	93.561	96.294
	Upper	23.014	9.322	3.899	1.636	1.008	0.550	0.265	0.195	0.035
	Lower	18.019	17.538	17.965	16.847	11.432	9.463	7.923	6.244	3.671
Panel B: Puts										
All Puts	In	47.473	60.014	67.502	75.967	83.314	87.472	90.354	93.315	96.918
	Upper	23.769	19.545	16.641	14.065	11.196	8.971	7.009	4.775	2.138
	Lower	28.758	20.441	15.858	9.969	5.491	3.557	2.637	1.910	0.944
OTM	In	58.478	70.985	76.330	84.561	91.651	94.207	95.614	96.625	98.430
	Upper	3.098	2.144	1.194	0.800	0.615	0.429	0.217	0.103	0.035
	Lower	38.425	26.871	22.476	14.639	7.735	5.364	4.169	3.272	1.534
ATM	In	23.460	39.771	51.280	61.740	72.206	80.700	86.177	92.194	97.604
	Upper	71.471	56.334	45.987	36.396	26.551	18.421	13.172	7.343	2.055
	Lower	5.070	3.896	2.733	1.865	1.244	0.879	0.651	0.463	0.341
ITM	In	46.703	55.336	65.462	74.694	79.357	82.078	84.109	85.646	89.591
	Upper	20.689	19.167	18.648	15.381	13.810	13.870	13.166	12.701	9.702
	Lower	32.608	25.497	15.891	9.925	6.833	4.052	2.726	1.653	0.707

Note: The table reports, for each maturity and for each class of options, the percentage of options over our sample for which 1-22 DTE prices fall within the SSD bounds (In), above the SSD upper bound (Upper) and below the SSD lower bound (Lower). The OTM put (ITM call), ATM and ITM put (OTM call) categories are defined as standardized log-moneyness below -1, between -1 and 1, and above 1, respectively. The sample ranges from January 6 2012 to March 18 2025.

Table 6: Sharpe ratios for SSD violation strategy

	10:00:00	10:30:00	11:00:00	11:30:00	12:00:00	12:30:00	13:00:00	13:30:00	14:00:00
Panel A: Before Transaction Costs									
Short ATM Call Delta-Hedge	0.002	−0.016	−0.015	−0.002	0.003	0.015	0.017	0.016	0.010
SSD ATM Call Delta-Hedge	0.161	0.141	0.125	0.142	0.142	0.139	0.147	0.188	0.190
Panel B: After Transaction Costs									
Short ATM Call Delta-Hedge	−0.037	−0.042	−0.039	−0.027	−0.023	−0.011	−0.010	−0.012	−0.033
SSD ATM Call Delta-Hedge	0.122	0.115	0.101	0.118	0.117	0.114	0.121	0.159	0.146

Note: The table reports, for each time of the day, before and after transaction costs, the Sharpe ratio associated with the SSD violation strategy based on the ATM call and the benchmark strategy writing the ATM call delta-hedged. To incorporate transaction costs, whenever we buy (sell) the option, we consider the ask (bid) price instead of the bid-ask midpoint, that is, we consider the worst case scenario for the strategy. The sample ranges from January 6 2012 to March 18 2025.

Table 7: Sharpe ratios for SSD violation strategy conditional on variables

	10:00:00	10:30:00	11:00:00	11:30:00	12:00:00	12:30:00	13:00:00	13:30:00	14:00:00
High 0DTE log-Volume	−0.044	−0.009	−0.019	−0.011	0.008	−0.012	−0.016	0.029	0.043
Low 0DTE log-Volume	0.327	0.265	0.241	0.277	0.250	0.289	0.316	0.332	0.269
High RV	0.020	0.009	0.004	0.026	0.044	0.030	0.023	0.082	0.070
Low RV	0.425	0.444	0.433	0.451	0.404	0.437	0.470	0.463	0.449
High VRP	0.072	0.073	0.065	0.058	0.070	0.074	0.081	0.129	0.103
Low VRP	0.196	0.178	0.166	0.216	0.196	0.183	0.189	0.218	0.238
High Google Trend Index	−0.005	0.023	0.012	0.025	0.026	0.002	0.007	0.045	0.049
Low Google Trend Index	0.250	0.204	0.181	0.200	0.199	0.222	0.238	0.273	0.235

Note: The table reports, for each time of the day, after transaction costs, the Sharpe ratio associated with the SSD violation strategy based on the ATM call, computed on days with a high (above median) or low (below median) value of a conditioning variable. To incorporate transaction costs, whenever we buy (sell) the option, we consider the ask (bid) price instead of the bid-ask midpoint, that is, we consider the worst case scenario for the strategy. 0DTE log-volume is the daily S&P 500 0DTE option log-volume, RV is the average of the realized variances we compute over the different times of the day, VRP is the average of the VRPs we compute over the different times of the day, and Google Trend Index is a sentiment index created using Google trends with the keyword "0DTE SPX options". The total sample ranges from January 6 2012 to March 18 2025.

Online Appendix to

0DTE Asset Pricing

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May 23, 2025

Abstract

This online appendix collects additional empirical results supporting the main paper.

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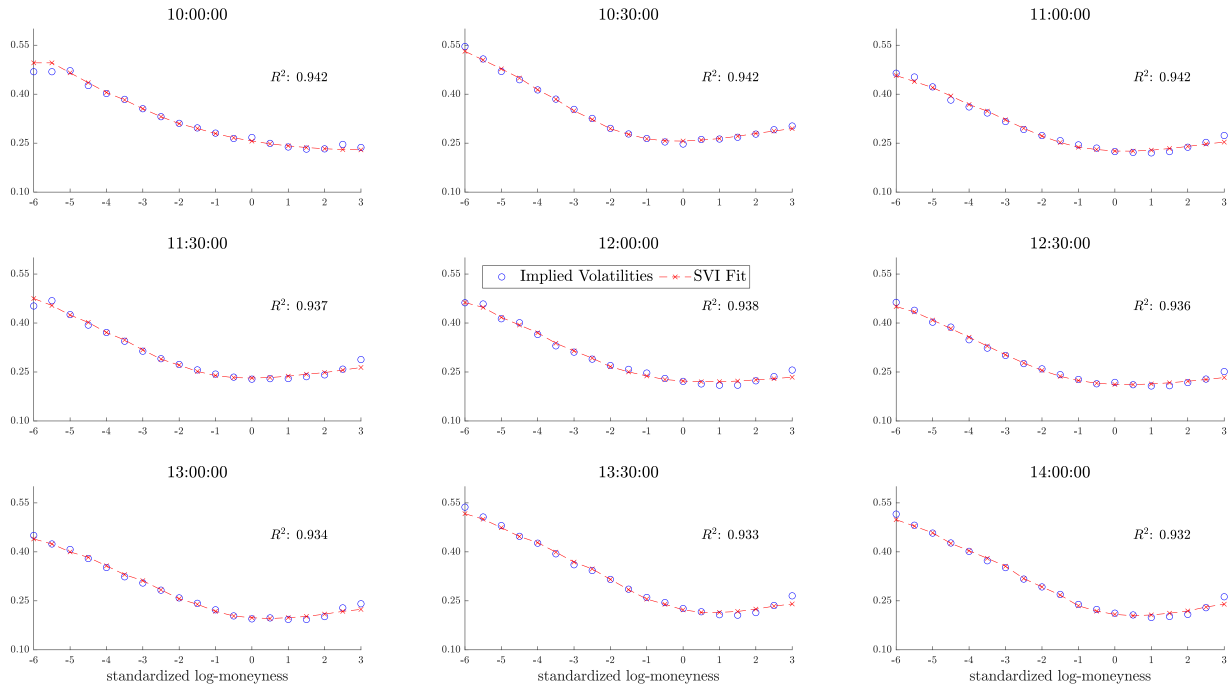
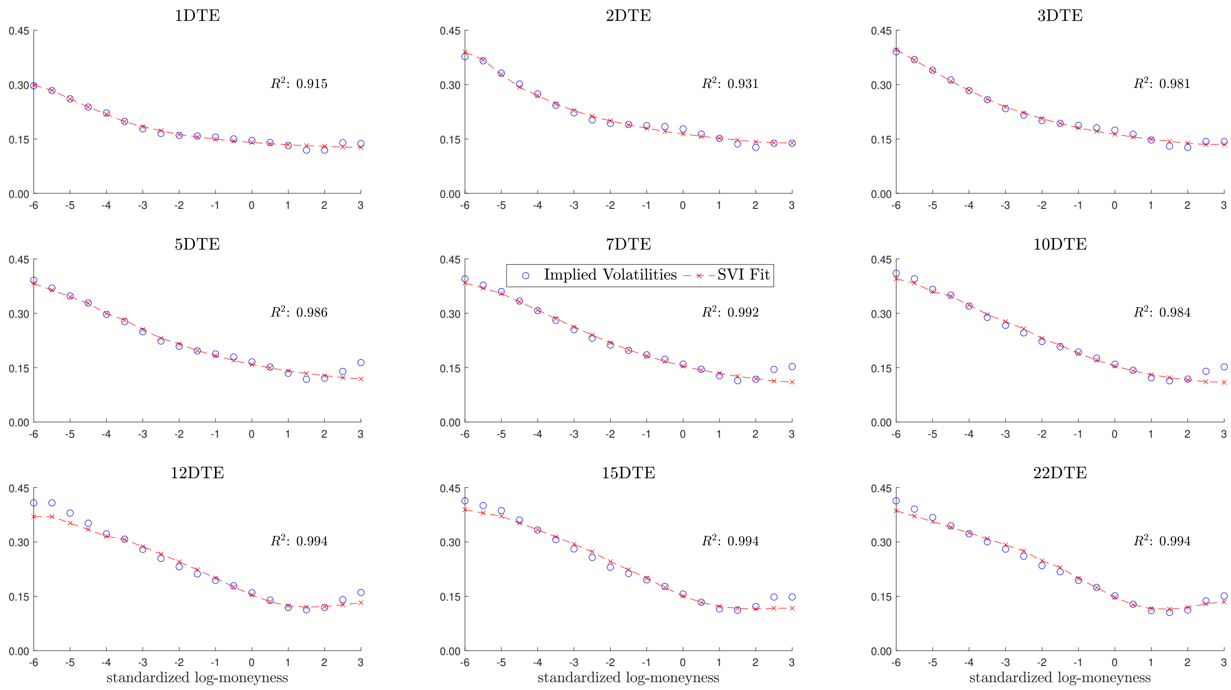
Figure OA.1: SVI fit



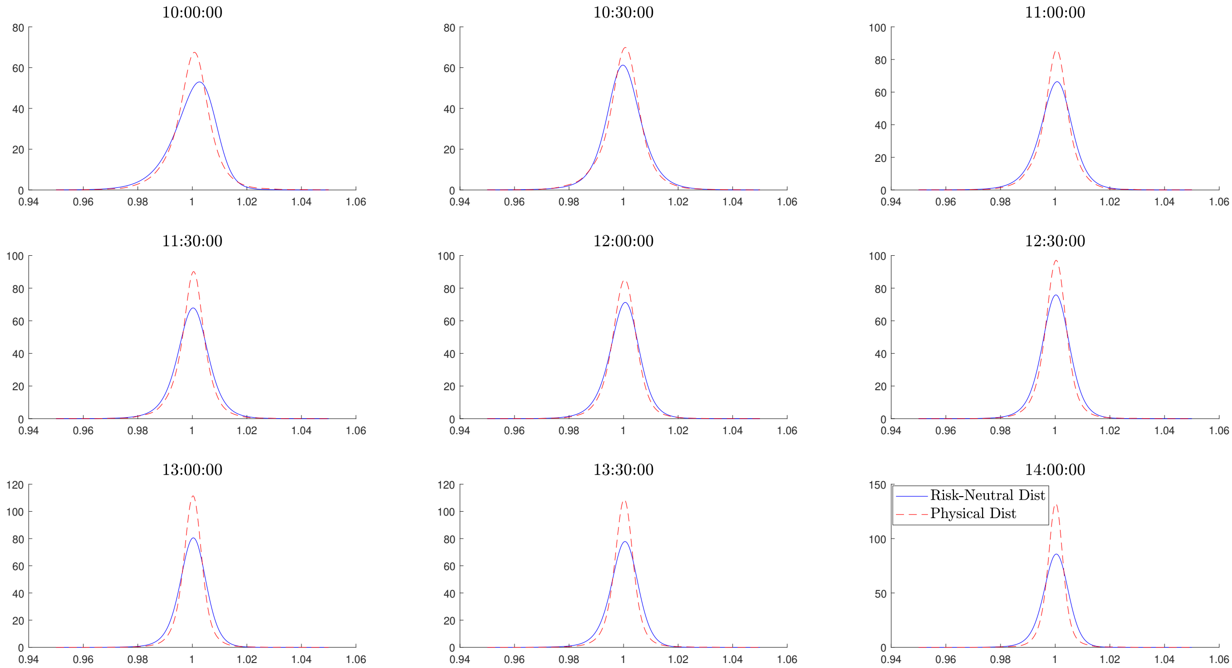
(a) 0DTEs



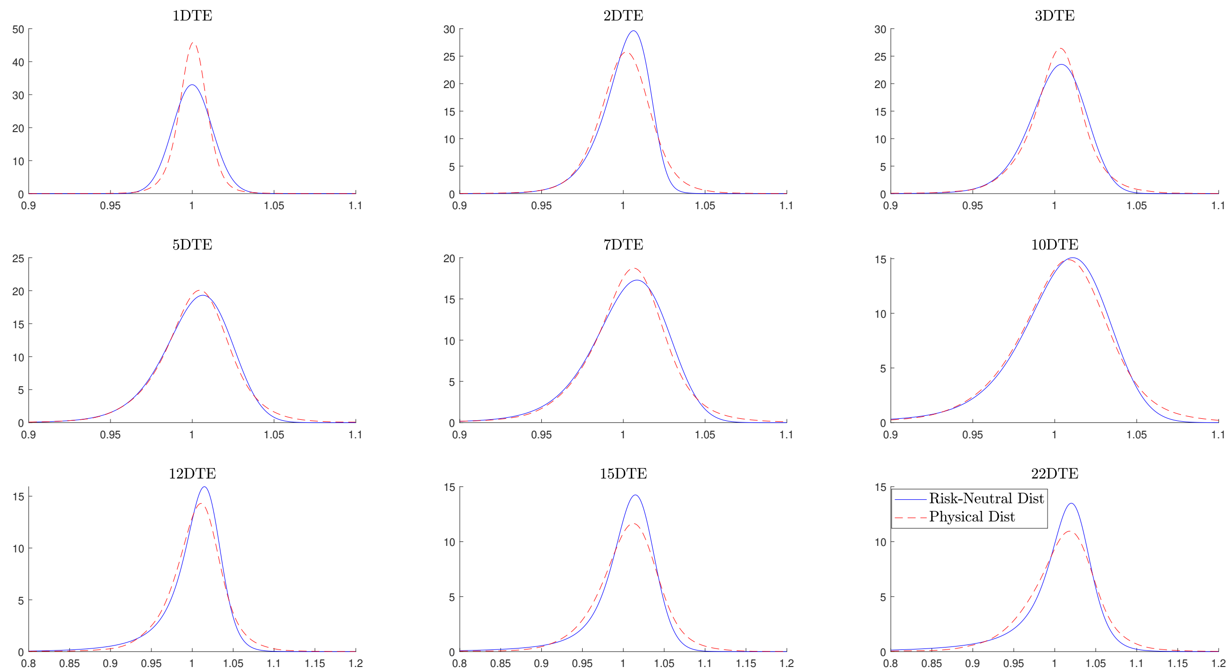
(b) 1-22 DTEs

Note: The figure plots, for a representative date of our sample, the observed IVs and the fitted IVs using the SVI method for 0DTEs (Panel a) and 1-22 DTEs (Panel b). The average OLS R^2 fit of the SVI over the entire sample is also reported. Standardized log-moneyness is defined as $\frac{\log(K/S_t)}{\sigma_{BS}(0)\sqrt{\tau}}$.

Figure OA.2: Market return risk-neutral and physical distributions



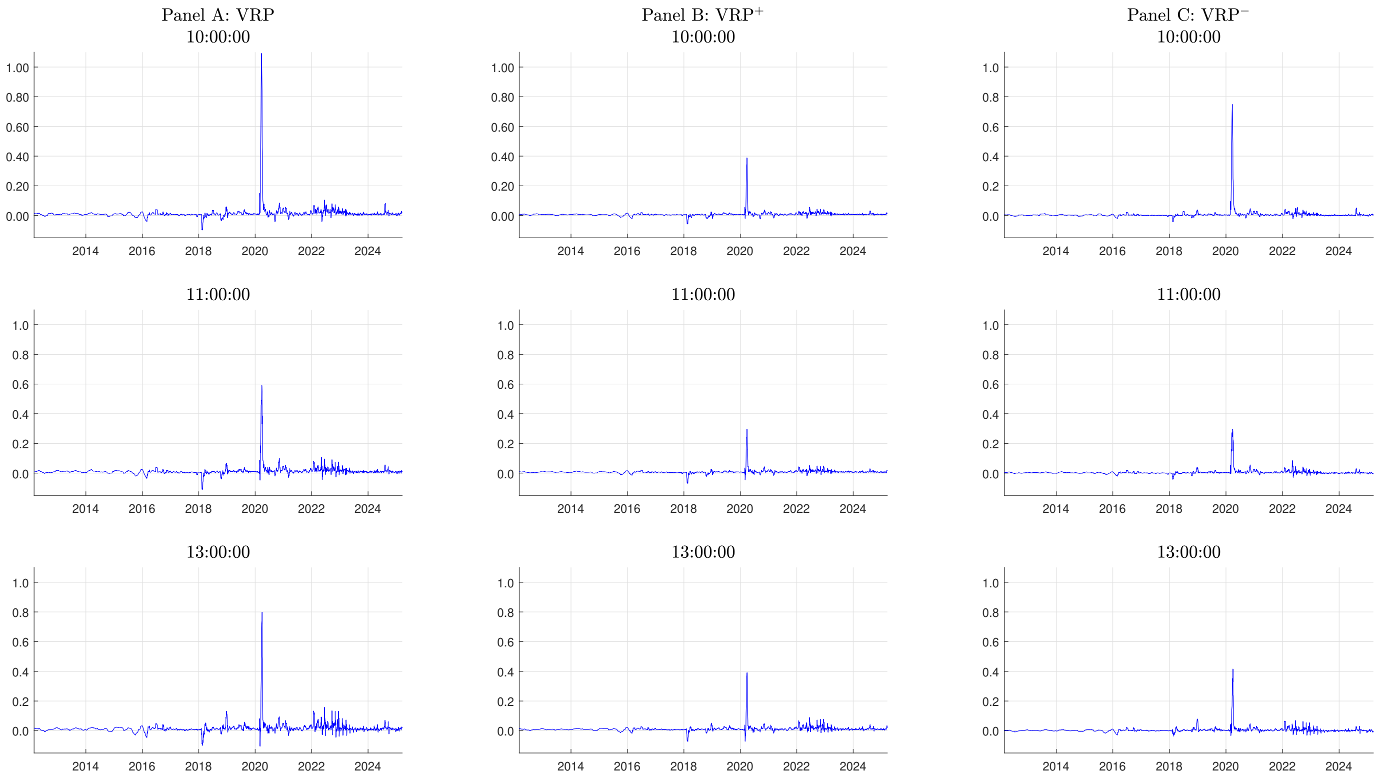
(a) 0DTEs



(b) 1-22 DTEs

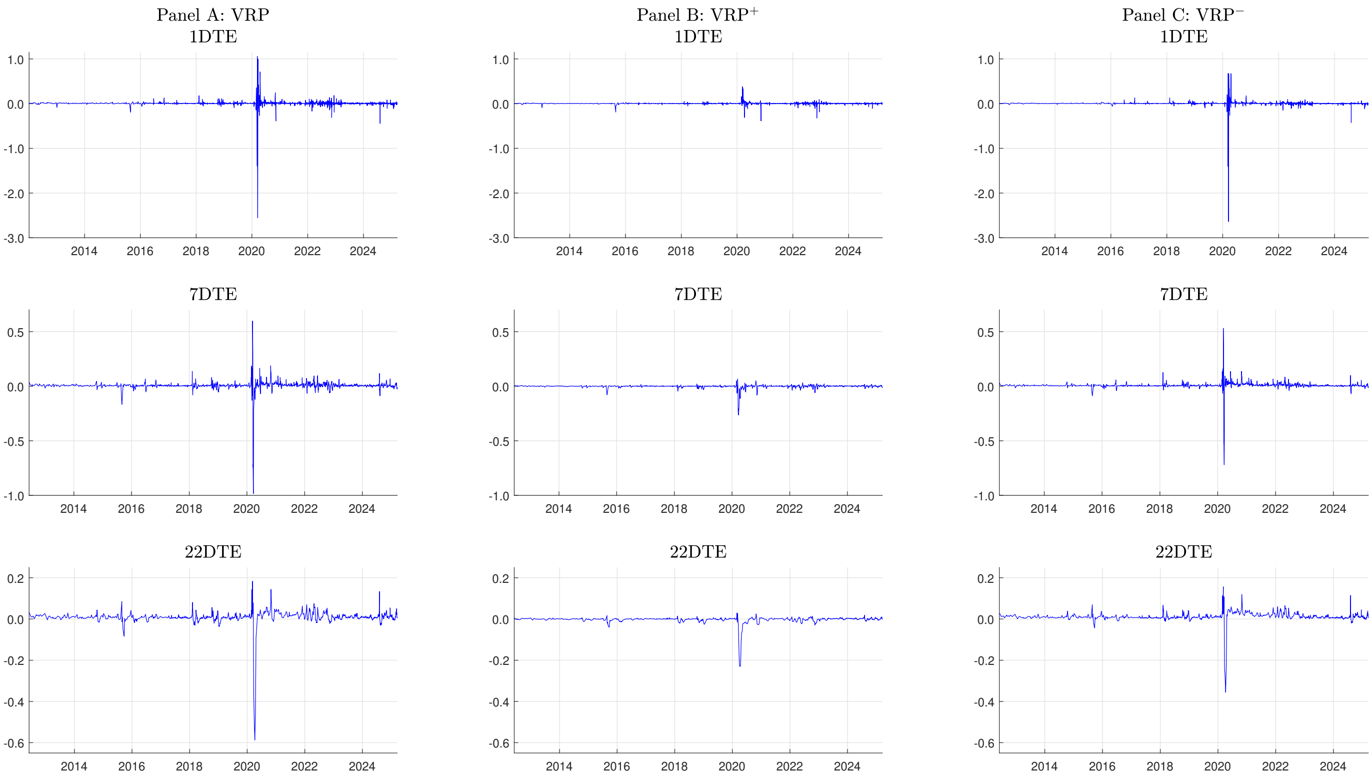
Note: The figure plots, for a representative date of our sample, the market return risk-neutral distribution and physical distribution estimated as described in Sections 3.3 and 3.4, respectively, for 0DTEs (Panel a) and 1-22 DTEs (Panel b). The horizontal axis represents gross market return states.

Figure OA.3: Intra-day variance risk premium over time



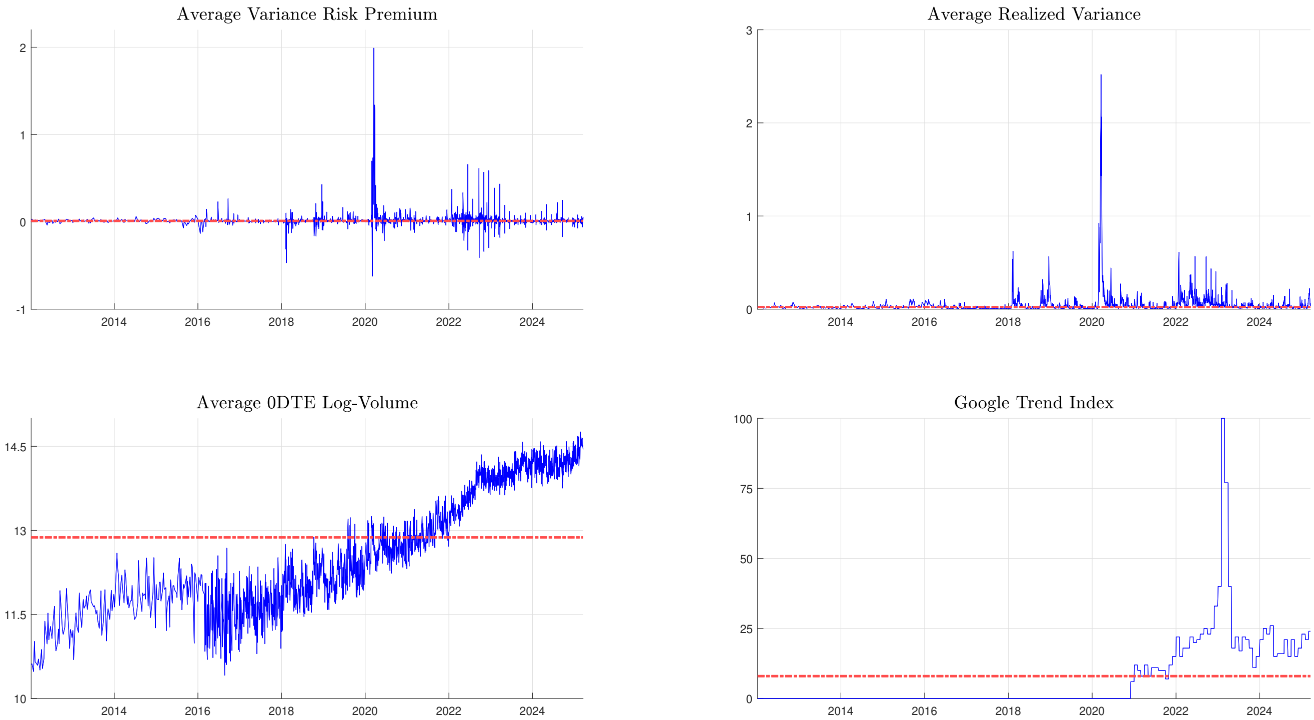
Note: The figure plots, for different times of the day, the one-week moving average (for ease of visualization) of the $VRP_{t,T}$, $VRP^{+}_{t,T}$ and $VRP^{-}_{t,T}$ over time. The measures are annualized. The sample ranges from January 6 2012 to March 18 2025.

Figure OA.4: Variance risk premium over time



Note: The figure plots the one-week moving average (for ease of visualization) of the $VRP_{t,T}$, $VRP^+_{t,T}$ and $VRP^-_{t,T}$ over time for different horizons as implied by longer-maturity options. The measures are annualized. The sample ranges from January 6 2012 to March 18 2025.

Figure OA.5: Conditioning variables



Note: The figure plots, for each of the conditioning variables in Table 7, their time-series together with a red dashed line indicating their median. The sample ranges from January 6 2012 to March 18 2025.

Table OA.1: Predicting excess market returns with risk measures

	10:00:00	10:30:00	11:00:00	11:30:00	12:00:00	12:30:00	13:00:00	13:30:00	14:00:00
RV	−0.023	−0.043	−0.052	−0.046	$-0.055^{\star}$	$-0.046^{\star}$	$-0.074^{\star\star}$	$-0.056^{\star}$	−0.040
t-stat	−0.495	−0.853	−1.063	−1.379	−1.691	−1.828	−2.016	−1.670	−1.184
$R^2(\%)$	0.090	0.350	0.549	0.496	0.789	0.612	1.788	1.090	0.619
$MFIS$	−0.015	−0.006	0.001	−0.012	0.002	0.007	0.002	−0.005	−0.013
t-stat	−0.950	−0.465	0.063	−0.948	0.179	0.680	0.209	−0.451	−1.291
$R^2(\%)$	0.037	0.008	0.000	0.033	0.001	0.014	0.002	0.008	0.068
$MFIK$	0.011	−0.018	−0.006	−0.011	−0.014	−0.016	−0.011	−0.010	0.001
t-stat	0.679	−1.130	−0.316	−0.914	−1.208	−1.568	−0.994	−1.029	0.080
$R^2(\%)$	0.020	0.062	0.008	0.030	0.051	0.074	0.038	0.035	0.000
$SVIX$	−0.013	−0.029	−0.043	−0.036	−0.044	−0.016	$-0.081^{\star\star\star}$	−0.032	−0.028
t-stat	−0.322	−0.625	−1.074	−1.408	−1.598	−0.747	−2.627	−0.956	−0.793
$R^2(\%)$	0.031	0.167	0.379	0.292	0.517	0.076	2.132	0.356	0.310

Note: The table reports, for each time of the day, the results from univariate predictive regressions over our sample using RV, $MFIS$ (risk-neutral skewness), $MFIK$ (risk-neutral kurtosis) and $SVIX$ to predict the excess market return from t to T. Regressors are standardized to have mean zero and unit variance. We compute the t-statistics using Newey-West robust standard errors with a lag length equal to 5. We denote with *, **, and *** significance at the 10%, 5% and 1% level, respectively. The sample ranges from January 6 2012 to March 18 2025.

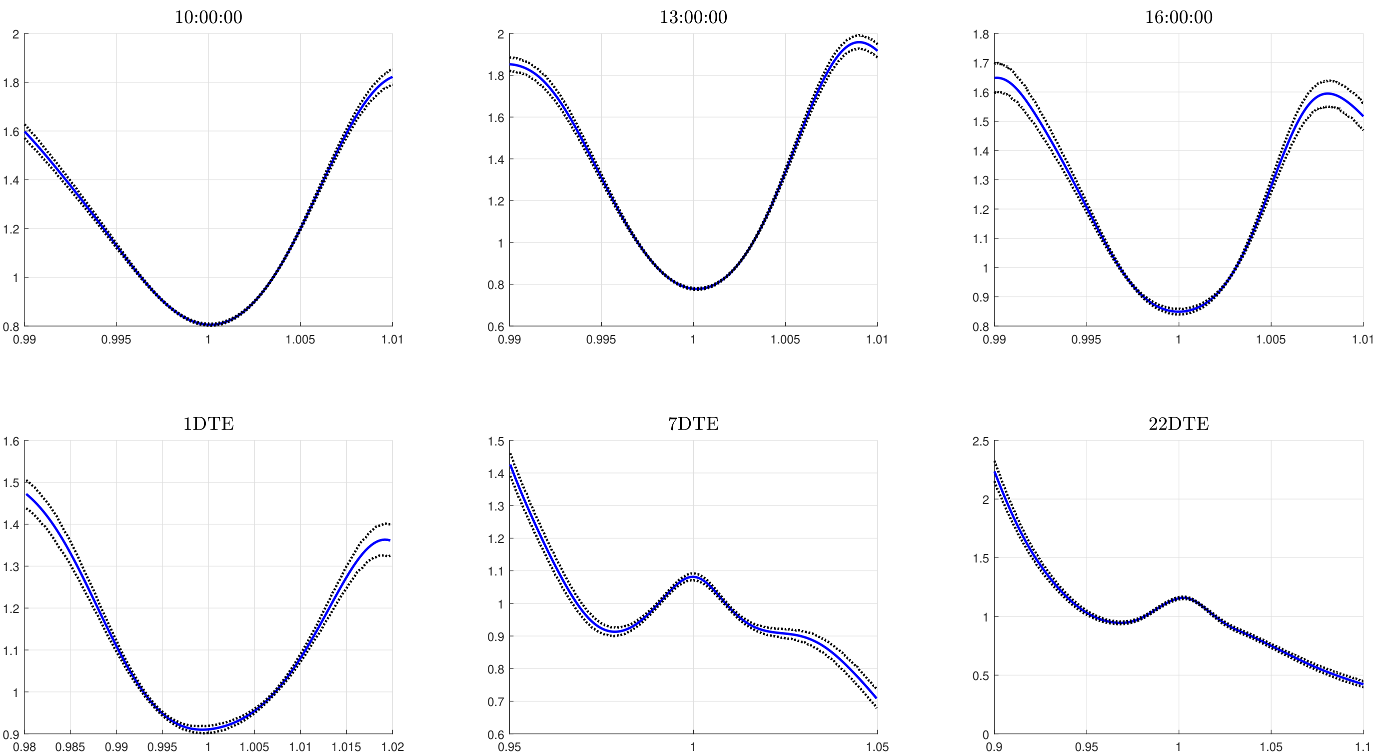
Table OA.2: Predicting excess market returns with variance risk premium and controls

	10:00:00		12:00:00		13:00:00		14:00:00	
VRP	$-0.118^{\star\star}$		$-0.149^{\star\star\star}$		$-0.064^{\star\star}$		$-0.104^{\star\star\star}$	
t-stat	-2.232		-3.221		-1.987		-3.381	
VRP^+		$-0.224^{\star\star\star}$		$-0.132^{\star\star}$		$-0.224^{\star\star\star}$		$-0.121^{\star\star\star}$
t-stat		-4.333		-2.153		-3.200		-2.908
VRP^-		$0.137^{\star\star}$		-0.016		$0.139^{\star\star\star}$		0.023
t-stat		2.272		-0.404		2.945		0.598
$MFIS$	-0.013	0.013	-0.001	0.007	-0.001	0.023	-0.020	-0.012
t-stat	-0.596	0.580	-0.049	0.359	-0.081	1.221	-1.276	-0.803
$MFIK$	0.007	0.013	-0.018	-0.017	-0.022	-0.011	-0.017	-0.014
t-stat	0.329	0.582	-1.088	-0.981	-1.331	-0.664	-1.095	-0.923
$SVIX$	0.086	0.031	$0.069^{\star}$	0.057	-0.038	-0.016	0.055	0.043
t-stat	1.249	0.496	1.648	1.617	-0.791	-0.520	1.304	1.125
$R^2(\%)$	0.617	2.756	2.772	3.036	2.758	5.151	1.734	2.087

Note: The table reports, for each time of the day, the results from multivariate predictive regressions over our sample based on $VRP_{t,T}$, $VRP^+_{t,T}$, $VRP^-_{t,T}$, $MFIS$ (risk-neutral skewness), $MFIK$ (risk-neutral kurtosis) and $SVIX$ to predict the excess market return from t to T. Regressors are standardized to have mean zero and unit variance. We compute the t-statistics using Newey-West robust standard errors with a lag length equal to 8. We denote with *, **, and *** significance at the 10%, 5% and 1% level, respectively. The sample ranges from January 6 2012 to March 18 2025.

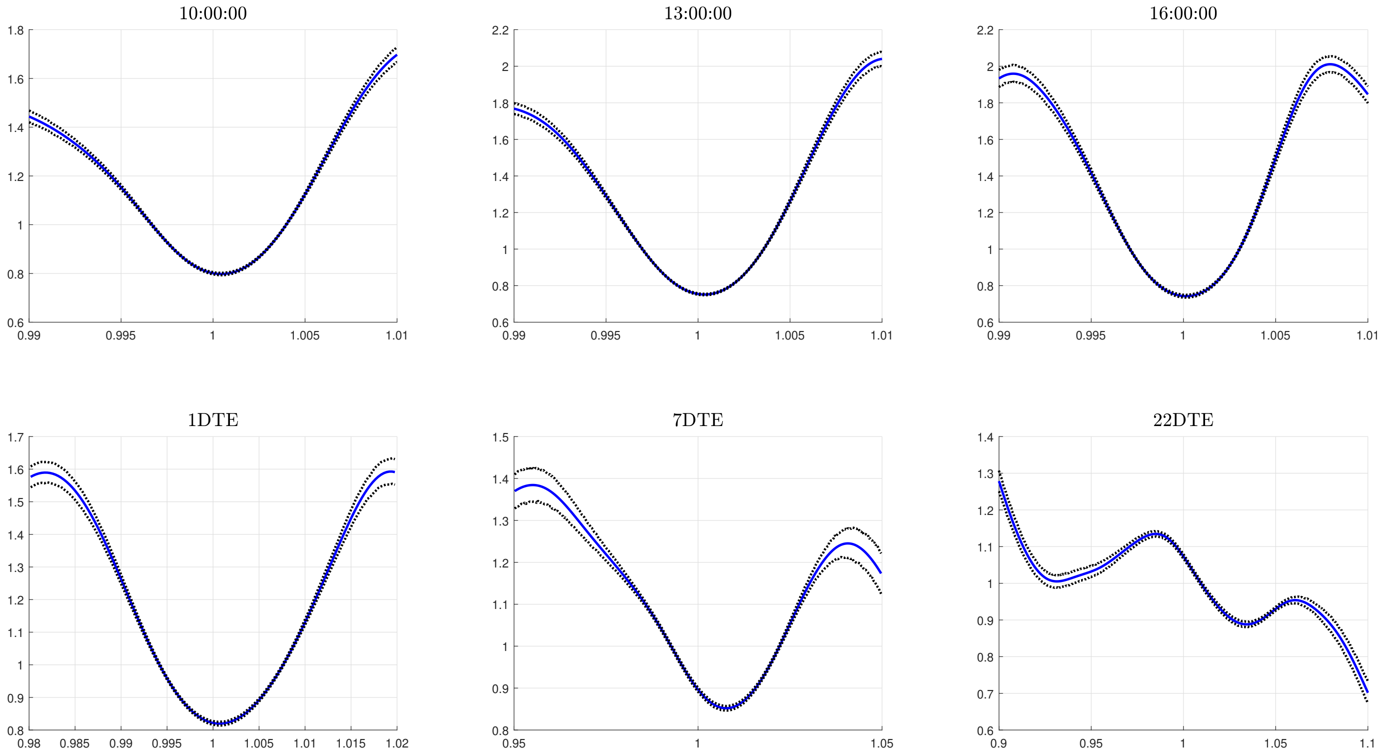
OA.1 Robustness - Before and after 2022

Figure OA.6: Average pricing kernels - before May 11 2022



Note: The figure plots, for different maturities, the average of the pricing kernel, as a function of market returns, over time before May 11 2022. The sample begins on January 6 2012.

Figure OA.7: Average pricing kernels - after May 11 2022



Note: The figure plots, for different maturities, the average of the pricing kernel, as a function of market returns, over time after May 11 2022. The sample ends on March 18 2025.

Table OA.3: Intra-day variance risk premium - before and after 2022

	10:00:00	11:00:00	12:00:00	13:00:00	14:00:00	10:00:00	11:00:00	12:00:00	13:00:00	14:00:00
	Before May 11, 2022					After May 11, 2022				
Panel A: VRP										
Mean	1.910	1.624	1.952	2.100	3.347	1.639	1.410	1.579	1.797	2.361
St. Dev.	11.130	9.594	9.977	10.975	15.066	4.434	4.718	6.092	8.329	13.351
25th Percentile	0.172	0.212	0.244	0.292	0.430	0.205	0.202	0.222	0.336	0.325
75th Percentile	1.857	1.802	2.193	2.419	3.263	2.272	2.226	2.362	2.587	3.087
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: VRP^{+}										
Mean	0.857	0.879	1.080	1.342	1.971	1.114	1.076	1.212	1.496	1.972
St. Dev.	4.426	4.088	4.617	5.405	7.903	2.141	2.415	3.027	4.167	6.465
25th Percentile	0.220	0.269	0.334	0.467	0.653	0.369	0.407	0.456	0.597	0.717
75th Percentile	1.082	1.141	1.375	1.666	2.258	1.489	1.512	1.731	1.936	2.393
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: VRP^{-}										
Mean	1.053	0.745	0.872	0.759	1.377	0.524	0.334	0.368	0.301	0.389
St. Dev.	7.230	6.117	5.717	5.980	7.691	2.533	2.409	3.417	4.272	7.036
25th Percentile	−0.067	−0.097	−0.122	−0.154	−0.256	−0.203	−0.260	−0.322	−0.372	−0.489
75th Percentile	0.766	0.708	0.846	0.877	1.093	0.886	0.726	0.693	0.665	0.729
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.032	0.075

Note: The table reports, for each time of the day for the 0DTEs, summary statistics of the $VRP_{t,T}$, $VRP^{+}_{t,T}$ and $VRP^{-}_{t,T}$ over our sample before May 11 2022 and after. The variance risk premium measures are annualized and expressed in percentage points. The p-values for the test with null hypothesis that the mean is smaller than or equal to zero, against the alternative that the mean is positive, are implemented using bootstrapped standard errors with 2,500 replications. The total sample ranges from January 6 2012 to March 18 2025.

Table OA.4: Variance risk premium - before and after 2022

	1DTE	3DTE	5DTE	10DTE	22DTE	1DTE	3DTE	5DTE	10DTE	22DTE
	Before May 11, 2022					After May 11, 2022				
Panel A: VRP										
Mean	0.644	0.443	0.495	0.533	0.723	0.422	0.530	0.481	0.695	0.937
St. Dev.	11.361	6.412	5.542	5.899	4.435	3.334	2.266	1.922	1.648	1.331
25th Percentile	0.096	0.137	0.100	0.220	0.358	−0.165	−0.068	−0.106	0.186	0.434
75th Percentile	1.398	1.283	1.228	1.471	1.483	1.449	1.222	1.166	1.227	1.440
p-value	0.061	0.021	0.003	0.003	0.000	0.001	0.000	0.000	0.000	0.000
Panel B: VRP^+										
Mean	0.307	−0.083	−0.229	−0.416	−0.377	0.280	0.157	0.047	−0.015	0.010
St. Dev.	2.761	2.304	2.024	2.367	1.854	2.088	1.303	1.094	0.827	0.530
25th Percentile	0.027	−0.086	−0.165	−0.297	−0.312	−0.004	−0.116	−0.183	−0.237	−0.218
75th Percentile	0.680	0.505	0.284	0.175	0.099	0.899	0.621	0.463	0.350	0.294
p-value	0.000	0.224	0.000	0.000	0.000	0.000	0.001	0.243	0.631	0.663
Panel C: VRP^-										
Mean	0.338	0.526	0.724	0.949	1.100	0.142	0.373	0.433	0.710	0.927
St. Dev.	10.735	4.981	4.214	3.986	2.807	2.297	1.517	1.202	1.077	0.980
25th Percentile	0.142	0.217	0.255	0.418	0.561	−0.067	0.040	0.073	0.306	0.496
75th Percentile	0.932	0.946	1.087	1.506	1.513	0.720	0.748	0.806	1.025	1.226
p-value	0.291	0.001	0.000	0.000	0.000	0.099	0.000	0.000	0.000	0.000

Note: The table reports, for each maturity, summary statistics of the $VRP_{t,T}$, $VRP^+_{t,T}$ and $VRP^-_{t,T}$ over our sample before May 11 2022 and after. The variance risk premium measures are annualized and expressed in percentage points. The p-values for the test with null hypothesis that the mean equals zero, against the alternative that the mean is different from zero, are implemented using bootstrapped standard errors with 2,500 replications. The total sample ranges from January 6 2012 to March 18 2025.

Table OA.5: Predicting excess market returns with variance risk premium - before and after 2022

	Before May 11, 2022						After May 11, 2022					
	10:00:00			11:00:00			10:00:00			11:00:00		
VRP	-0.054			-0.079^{**}			$-0.047^{\star}$			-0.049^{**}		
t-stat	-1.482			-2.343			-1.735			-2.165		
VRP^{+}		-0.108^{***}			-0.138^{***}			-0.058^{**}			-0.037	
t-stat		-2.604			-3.331			-1.977			-1.577	
VRP^{-}			-0.017			-0.031			-0.033			-0.059^{***}
t-stat			-0.403			-1.073			-1.339			-2.644
$R^2(\%)$	0.506	2.004	0.052	1.205	3.703	0.190	0.384	0.594	0.188	0.550	0.320	0.784
	11:30:00			12:30:00			11:30:00			12:30:00		
VRP	$-0.066^{\star}$			-0.038			-0.037			-0.044^{**}		
t-stat	-1.862			-1.568			-1.566			-2.455		
VRP^{+}		$-0.091^{\star}$			-0.043			-0.043^{**}			-0.041^{**}	
t-stat		-1.740			-1.176			-2.008			-2.187	
VRP^{-}			-0.018			-0.015			-0.028			-0.046^{***}
t-stat			-0.583			-0.469			-0.994			-2.621
$R^2(\%)$	0.913	1.723	0.069	0.377	0.496	0.058	0.367	0.514	0.208	0.619	0.523	0.684
	13:00:00			14:00:00			13:00:00			14:00:00		
VRP	-0.109^{***}			-0.071^{**}			-0.051^{***}			-0.042^{**}		
t-stat	-5.037			-2.024			-2.802			-2.004		
VRP^{+}		-0.140^{***}			-0.083^{**}			-0.049^{***}			-0.040^{**}	
t-stat		-4.502			-2.561			-2.667			-2.120	
VRP^{-}			-0.074^{***}			-0.054			-0.052^{***}			$-0.042^{\star}$
t-stat			-3.156			-1.381			-2.807			-1.881
$R^2(\%)$	3.753	6.127	1.738	1.786	2.441	1.026	0.907	0.829	0.939	0.820	0.778	0.823

Note: The table reports, for each time of the day, the results from different predictive regressions over our sample before May 11 2022 and after using $VRP_{t,T}$, $VRP^{+}_{t,T}$ and $VRP^{-}_{t,T}$ to predict the excess market return from t to T. Regressors are standardized to have mean zero and unit variance. We compute the t-statistics using Newey-West robust standard errors with a lag length equal to 8. We denote with *, **, and *** significance at the 10%, 5% and 1% level, respectively. The total sample ranges from January 6 2012 to March 18 2025.

Table OA.6: Option price bounds for 0DTE options - before and after 2022

		10:00:00	11:00:00	12:00:00	13:00:00	14:00:00	10:00:00	11:00:00	12:00:00	13:00:00	14:00:00
		Before May 11, 2022					After May 11, 2022				
Panel A: Calls											
All Calls	In	14.848	15.157	17.692	14.583	15.652	30.736	33.953	32.071	25.113	28.011
	Upper	41.985	41.364	39.161	43.057	40.680	40.361	38.654	39.033	43.725	46.453
	Lower	43.167	43.479	43.147	42.360	43.668	28.903	27.393	28.896	31.163	25.536
OTM	In	27.064	29.611	34.266	29.323	28.934	33.725	40.636	38.134	29.704	30.647
	Upper	7.322	9.654	8.738	8.703	9.802	3.210	6.939	7.700	6.091	6.201
	Lower	65.613	60.735	56.996	61.974	61.264	63.065	52.425	54.165	64.205	63.152
ATM	In	5.453	4.716	6.248	4.854	4.695	8.947	5.213	4.157	2.788	2.809
	Upper	66.582	65.971	67.376	71.835	68.395	89.601	94.026	95.239	96.748	96.536
	Lower	27.965	29.313	26.376	23.311	26.910	1.451	0.761	0.604	0.465	0.655
ITM	In	14.158	13.876	15.944	12.763	15.067	40.259	44.140	41.913	32.908	38.056
	Upper	45.011	43.328	38.831	44.318	40.929	33.675	27.479	27.620	36.641	41.859
	Lower	40.831	42.796	45.224	42.919	44.004	26.066	28.381	30.468	30.450	20.085
Panel B: Puts											
All Puts	In	30.639	31.598	35.108	31.654	33.417	33.565	35.331	34.552	30.830	35.985
	Upper	34.467	36.927	36.444	37.397	37.181	29.885	31.758	31.778	34.012	31.791
	Lower	34.894	31.475	28.448	30.949	29.402	36.550	32.911	33.669	35.158	32.223
OTM	In	51.563	53.967	60.132	54.414	57.348	44.194	46.578	47.016	43.687	52.233
	Upper	15.882	18.180	15.182	18.447	17.780	6.395	9.782	10.001	14.425	10.843
	Lower	32.554	27.854	24.686	27.139	24.872	49.411	43.640	42.983	41.888	36.924
ATM	In	6.005	4.996	5.616	4.561	4.143	9.937	5.911	5.078	3.188	4.044
	Upper	68.672	73.421	76.431	75.655	75.321	85.956	92.047	93.398	95.002	93.522
	Lower	25.323	21.584	17.953	19.783	20.537	4.107	2.042	1.525	1.810	2.434
ITM	In	7.179	8.719	10.051	8.468	9.161	37.674	44.373	39.596	32.273	31.610
	Upper	36.905	36.201	37.211	34.962	35.870	15.165	10.358	9.922	6.660	8.182
	Lower	55.916	55.081	52.737	56.569	54.968	47.161	45.269	50.482	61.067	60.208

Note: The table reports, for each time of the day and for each class of options, the percentage of 0DTE options over our sample before May 11 2022 and after for which prices fall within the SSD bounds (In), above the SSD upper bound (Upper) and below the SSD lower bound (Lower). The OTM put (ITM call), ATM and ITM put (OTM call) categories are defined as standardized log-moneyness below -1, between -1 and 1, and above 1, respectively. The total sample ranges from January 6 2012 to March 18 2025.

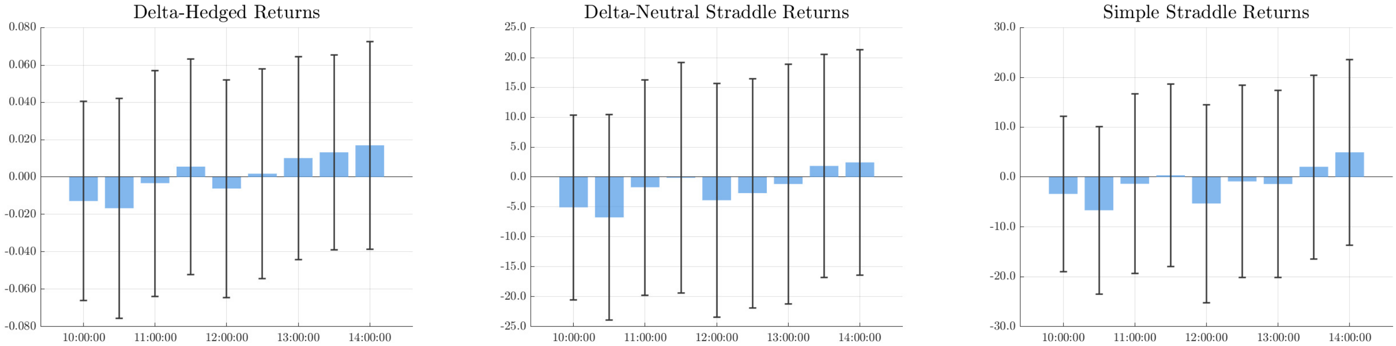
Table OA.7: Option price bounds for 1-22 DTE options - before and after 2022

		1DTE	3DTE	5DTE	10DTE	22DTE	1DTE	3DTE	5DTE	10DTE	22DTE
		Before May 11, 2022					After May 11, 2022				
All Calls	In	54.592	77.206	83.680	92.089	98.009	42.979	63.550	68.562	80.873	95.726
	Upper	32.110	14.333	9.550	4.597	0.826	35.495	20.196	17.403	11.315	1.285
	Lower	13.298	8.461	6.770	3.314	1.166	21.525	16.254	14.035	7.812	2.989
OTM	In	67.969	84.196	89.627	94.173	97.975	57.327	84.287	91.301	95.884	99.879
	Upper	3.852	2.755	1.998	2.028	1.016	3.929	1.779	1.602	1.341	0.084
	Lower	28.179	13.049	8.375	3.798	1.010	38.744	13.934	7.097	2.775	0.036
ATM	In	19.362	55.326	68.796	86.035	97.667	13.214	36.380	48.820	73.554	97.305
	Upper	78.534	42.572	29.017	12.691	1.857	85.664	62.490	50.444	26.229	2.638
	Lower	2.104	2.101	2.187	1.274	0.476	1.123	1.130	0.735	0.217	0.057
ITM	In	66.510	85.841	89.277	94.988	98.264	51.559	69.960	72.087	82.201	92.266
	Upper	21.322	4.331	2.128	0.632	0.026	24.675	3.440	1.039	0.422	0.053
	Lower	12.168	9.828	8.594	4.380	1.710	23.766	26.600	26.875	17.377	7.682
Panel B: Puts											
All Puts	In	57.742	77.239	83.364	91.464	97.550	37.675	57.605	67.796	82.241	95.897
	Upper	24.996	15.168	11.674	6.725	1.952	22.598	18.137	16.705	11.915	2.438
	Lower	17.262	7.593	4.962	1.811	0.498	39.726	24.258	15.499	5.845	1.665
OTM	In	74.750	89.994	94.257	98.323	99.625	43.195	62.090	72.988	87.860	96.005
	Upper	5.413	2.113	1.272	0.544	0.036	0.923	0.236	0.237	0.251	0.034
	Lower	19.836	7.894	4.471	1.133	0.339	55.882	37.673	26.775	11.888	3.961
ATM	In	26.030	58.587	69.660	85.829	97.743	20.998	44.435	54.355	75.731	97.440
	Upper	68.758	38.309	27.563	12.715	1.721	74.068	53.180	44.631	23.949	2.450
	Lower	5.211	3.104	2.777	1.456	0.536	4.934	2.385	1.014	0.320	0.110
ITM	In	48.040	65.121	71.500	80.876	89.807	45.357	65.826	78.441	84.006	89.161
	Upper	23.840	21.433	18.676	14.619	9.233	17.515	15.668	11.515	12.668	10.634
	Lower	28.120	13.446	9.823	4.505	0.959	37.128	18.506	10.044	3.325	0.205

Note: The table reports, for each maturity and for each class of options, the percentage of 1-22 DTE options over our sample before May 11 2022 and after for which prices fall within the SSD bounds (In), above the SSD upper bound (Upper) and below the SSD lower bound (Lower). The OTM put (ITM call), ATM and ITM put (OTM call) categories are defined as standardized log-moneyness below -1, between -1 and 1, and above 1, respectively. The total sample ranges from January 6 2012 to March 18 2025.

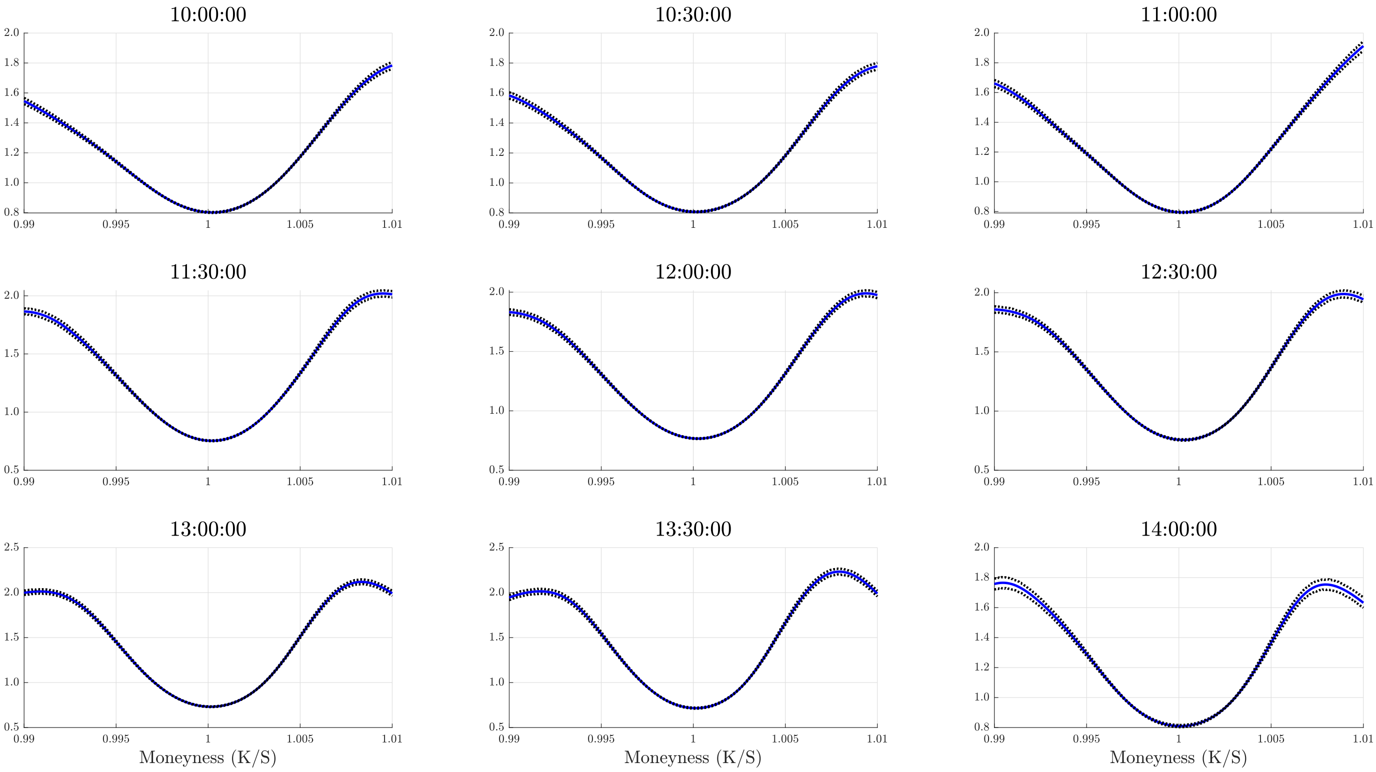
OA.2 Robustness - FOMC announcement days

Figure OA.8: Average returns of 0DTE option strategies - FOMC announcement days



Note: The figure plots, for different times of the day, the average returns together with 90% confidence bands for ATM delta-hedged calls, delta-neutral straddles and simple straddles, for FOMC announcement days. Confidence bands are based on 2,500 bootstrap replications. The total sample ranges from January 6 2012 to March 18 2025.

Figure OA.9: Average intra-day pricing kernels - removing FOMC days



Note: The figure plots, for different times of the day, the average of the pricing kernel, as a function of market returns, over time removing FOMC announcement days. The total sample ranges from January 6 2012 to March 18 2025.

Table OA.8: Intra-day variance risk premium - removing FOMC days

	10:00:00	10:30:00	11:00:00	11:30:00	12:00:00	12:30:00	13:00:00	13:30:00	14:00:00
Panel A: VRP									
Mean	1.591	1.311	1.254	1.365	1.432	1.772	1.439	1.783	1.967
St. Dev.	9.104	7.478	7.839	8.701	8.245	13.545	9.113	11.091	12.044
25th Percentile	0.151	0.129	0.170	0.165	0.196	0.232	0.262	0.289	0.334
75th Percentile	1.885	1.752	1.826	1.987	2.097	2.118	2.283	2.517	2.927
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: VRP^+									
Mean	0.848	0.809	0.811	0.977	0.943	1.321	1.134	1.310	1.473
St. Dev.	3.656	3.423	3.384	5.494	3.828	9.933	4.504	5.508	6.132
25th Percentile	0.249	0.287	0.298	0.340	0.354	0.393	0.489	0.576	0.661
75th Percentile	1.160	1.178	1.196	1.330	1.411	1.491	1.681	1.873	2.176
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: VRP^-									
Mean	0.743	0.502	0.443	0.387	0.489	0.451	0.305	0.474	0.494
St. Dev.	5.903	4.607	4.961	4.020	4.788	5.300	4.955	5.846	6.318
25th Percentile	−0.128	−0.182	−0.185	−0.195	−0.248	−0.253	−0.277	−0.318	−0.375
75th Percentile	0.742	0.659	0.640	0.670	0.685	0.631	0.662	0.755	0.793
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.001

Note: The table reports, for each time of the day for the 0DTEs, summary statistics of the $VRP_{t,T}$, $VRP^+_{t,T}$ and $VRP^-_{t,T}$ over our sample removing FOMC days. The variance risk premium measures are annualized and expressed in percentage points. The p-values for the test with null hypothesis that the mean is smaller than or equal to zero, against the alternative that the mean is positive, are implemented using bootstrapped standard errors with 2,500 replications. The total sample ranges from January 6 2012 to March 18 2025.

Table OA.9: Predicting excess market returns with variance risk premium - removing FOMC days

	10:00:00				10:30:00				11:00:00			
VRP	−0.040				−0.034				−0.058**			
t-stat	−1.430				−1.063				−2.388			
VRP^{+}		−0.081***		−0.205***		−0.061*		−0.117		−0.096***		−0.180**
t-stat		−2.589		−3.615		−1.749		−1.591		−2.839		−2.502
VRP^{-}			−0.011	0.154***			−0.009	0.076			−0.025	0.111**
t-stat			−0.328	3.209			−0.306	0.977			−1.199	2.021
$R^2(\%)$	0.281	1.176	0.021	2.659	0.226	0.751	0.016	1.294	0.710	1.988	0.137	3.120
	11:30:00				12:00:00				12:30:00			
VRP	−0.046*				−0.090***				−0.026			
t-stat	−1.958				−3.426				−1.490			
VRP^{+}		−0.065*		−0.104*		−0.098***		−0.109		−0.031		−0.037
t-stat		−1.775		−1.646		−2.938		−1.635		−1.150		−0.835
VRP^{-}			−0.011	0.058*			−0.077***	0.014			−0.009	0.011
t-stat			−0.533	1.675			−3.394	0.271			−0.373	0.280
$R^2(\%)$	0.516	1.027	0.029	1.482	2.259	2.667	1.646	2.683	0.211	0.294	0.025	0.319
	13:00:00				13:30:00				14:00:00			
VRP	−0.083***				−0.043				−0.064**			
t-stat	−4.017				−1.499				−2.571			
VRP^{+}		−0.104***		−0.202***		−0.057**		−0.180***		−0.072***		−0.106***
t-stat		−3.577		−3.032		−2.192		−3.111		−3.126		−2.986
VRP^{-}			−0.058***	0.115**			−0.028	0.136**			−0.053*	0.039
t-stat			−2.922	2.334			−0.903	2.436			−1.920	1.076
$R^2(\%)$	2.425	3.806	1.190	5.064	0.711	1.248	0.300	2.498	1.848	2.294	1.258	2.458

Note: The table reports, for each time of the day, the results from different predictive regressions over our sample removing FOMC announcement days using $VRP_{t,T}$, $VRP^{+}_{t,T}$ and $VRP^{-}_{t,T}$ to predict the excess market return from t to T. Regressors are standardized to have mean zero and unit variance. We compute the t-statistics using Newey-West robust standard errors with a lag length equal to 5. We denote with ⋆, ⋆⋆, and ⋆⋆⋆ significance at the 10%, 5% and 1% level, respectively. The total sample ranges from January 6 2012 to March 18 2025.

Table OA.10: Option price bounds for 0DTE options - removing FOMC days

		10:00:00	10:30:00	11:00:00	11:30:00	12:00:00	12:30:00	13:00:00	13:30:00	14:00:00
Panel A: Calls										
All Calls	In	23.762	24.914	26.079	27.750	26.347	30.523	21.084	16.865	22.821
	Upper	41.255	39.997	39.973	39.077	39.047	36.739	43.527	46.574	43.698
	Lower	34.983	35.089	33.948	33.173	34.606	32.738	35.389	36.561	33.481
OTM	In	31.509	34.654	37.036	39.650	37.839	42.981	30.778	21.357	30.749
	Upper	5.113	6.959	8.314	7.684	8.372	6.820	7.526	7.142	7.979
	Lower	63.379	58.387	54.650	52.665	53.789	50.199	61.697	71.501	61.271
ATM	In	7.340	6.795	4.987	5.571	5.211	6.401	3.782	2.815	3.689
	Upper	78.745	78.674	80.734	80.597	81.638	81.686	84.314	84.438	83.316
	Lower	13.915	14.531	14.279	13.833	13.151	11.913	11.904	12.747	12.995
ITM	In	28.451	29.172	31.138	32.907	31.070	36.170	24.760	21.413	28.113
	Upper	39.341	36.451	34.911	33.527	32.860	29.181	40.630	46.676	41.307
	Lower	32.208	34.377	33.950	33.566	36.070	34.649	34.610	31.912	30.580
Panel B: Puts										
All Puts	In	32.924	34.390	34.597	37.681	35.992	40.506	32.359	29.165	36.050
	Upper	31.893	32.882	34.115	33.176	33.969	31.127	35.644	38.006	33.771
	Lower	35.183	32.727	31.288	29.143	30.039	28.367	31.997	32.829	30.179
OTM	In	48.634	50.366	51.239	56.620	54.464	61.025	50.015	46.547	56.208
	Upper	10.855	12.558	13.799	11.869	12.560	8.863	16.466	21.408	13.759
	Lower	40.511	37.077	34.962	31.511	32.976	30.112	33.519	32.045	30.034
ATM	In	8.180	7.305	5.516	5.932	5.437	6.910	3.883	3.019	4.038
	Upper	77.730	80.586	83.098	83.610	85.397	83.676	85.709	84.897	84.757
	Lower	14.091	12.109	11.385	10.458	9.166	9.414	10.408	12.084	11.205
ITM	In	23.965	27.747	29.049	28.960	27.278	29.791	22.249	15.879	21.954
	Upper	25.307	22.534	22.599	22.936	22.911	21.286	20.742	20.081	20.550
	Lower	50.728	49.720	48.352	48.104	49.810	48.923	57.009	64.040	57.496

Note: The table reports, for each time of the day and for each class of options, the percentage of options over our sample, removing FOMC announcement days, for which prices fall within the SSD bounds (In), above the SSD upper bound (Upper) and below the SSD lower bound (Lower). The OTM put (ITM call), ATM and ITM put (OTM call) categories are defined as standardized log-moneyness below -1, between -1 and 1, and above 1, respectively. The total sample ranges from January 6 2012 to March 18 2025.

Table OA.11: Sharpe ratios for SSD violation strategy - removing FOMC days

	10:00:00	10:30:00	11:00:00	11:30:00	12:00:00	12:30:00	13:00:00	13:30:00	14:00:00
Panel A: Before Transaction Costs									
Short ATM Call Delta-Hedge	-0.001	-0.019	-0.015	-0.002	0.001	0.014	0.020	0.027	0.024
SSD ATM Call Delta-Hedge	0.166	0.146	0.131	0.153	0.145	0.147	0.156	0.194	0.201
Panel B: After Transaction Costs									
Short ATM Call Delta-Hedge	-0.040	-0.045	-0.040	-0.027	-0.025	-0.013	-0.008	-0.003	-0.012
SSD ATM Call Delta-Hedge	0.128	0.120	0.107	0.128	0.120	0.122	0.129	0.165	0.166

Note: The table reports, for each time of the day, before and after transaction costs, the Sharpe ratio associated with the SSD violation strategy based on the ATM call and the benchmark strategy writing the ATM call delta-hedged. To incorporate transaction costs, whenever we buy (sell) the option, we consider the ask (bid) price instead of the bid-ask midpoint, that is, we consider the worst case scenario for the strategy. The sample ranges from January 6 2012 to March 18 2025 excluding FOMC announcement days.