# Does 0DTE Options Trading Increase Volatility?

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ABSTRACT

This paper examines the impact of Zero-Day-to-Expiration (0DTE) options trading on stock market volatility. The monthly trading volume of 0DTE options linked to the S&P 500 index increased from .08 million contracts in January 2011 to 23.5 million contracts in December 2022 and now accounts for 40% of the trading in S&P 500 index options. Using historical 0DTE option volume to overcome endogeneity issues, we show that a one standard deviation increase in 0DTE options trading increases volatility by 24.5%. The effect is 3.5 times the magnitude that Harris (1989) shows regarding the general options trading impact on volatility.

**Keywords**: Zero-Day-to-Expiration (0DTE) Options, Volatility, Market Efficiency

**JEL classification**: G12, G13, G14, G17

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# 1. Introduction

In December 2010, the Chicago Board Options Exchange (CBOE) introduced short-dated option products, SPXW, linked to the S&P500 index. These new option products have a life ranging from one week to one month, dramatically shorter than the previously available S&P 500 linked option, whose lifespans range from three months to three years. The increase in options with varying expiration days has led to more opportunities for investors to trade near the expiration of an option, especially Zero-Day-to-Expiration (0DTE) options. 0DTE options are referred to as options traded on the last day before expiring. 0DTE options trading has recently exploded in popularity. While there is extant literature exploring the influence of options on their underlying assets[1], there is little work examining the impact of short-term expiration options on the underlying assets. This paper examines whether 0DTE options trading affects the volatility of the stock market.

There is a long-running debate about whether derivative securities impact their underlying asset. The traditional view is that the underlying assets are independent of derivative securities that they are written on. For example, Black and Sholes (1973) framework argues that since all derivative securities can be spanned by underlying assets, they are redundant products that do not affect their underlying asset. Furthermore, Cox and Ross (1976) support this idea by modeling the stochastic price process independently and showing that the price of an option is a function of its underlying stock. The model implies that option contracts do not affect the price of the underlying stock because an underlying stock and an option written on it are perfectly correlated.

In contrast, the alternative view argues that derivative securities affect their underlying asset. Danthine (1978) provides a theoretical model showing that the derivative markets contribute to the reduction in spot volatility since the reduced transaction costs in derivatives trading allow the

[1] The general relationship between options trading and the volatility of the underlying asset is well studied (Day and Lewis 1988; Skinner 1989; Conrad 1989; Harris 1989; Kamara, Miller, and Siegel 1992; Kumar et al. 1998; Ni, Pan, and Poteshman 2008; Muravyev, Pearson, and Broussard 2013). Regarding the relationship between the volatility of underlying assets and options trading, the literature reveals mixed and divergent results. For instance, Kumar et al. (1998), Skinner (1989), and Conrad (1989) argue that options trading leads to the reduction in the volatility of underlying assets. On the other hand, Day and Lewis (1988), Harris (1989), and Ni et al. (2008) document that options trading is positively related to the volatility of underlying assets. However, Kamara et al. (1992), Long et al. (1994), Darrat and Rahman (1995), and Muravyev et al. (2013) find no clear evidence on the relationship.

informed traders to respond to the mispricing more efficiently. Stein (1987) argues that the introduction of a future market decreases spot price volatility because of risk sharing between speculators and informed traders. He concludes that the introduction would lead to heightened volatility when the speculators trade based on information with noise, but hedgers respond to this noise in the speculative trades. Ross (1989) models information flowing from the derivatives market and affecting the underlying market. If information is contained in the derivatives trading then the price of the spot market is affected, and the volatility of the spot market increases. More recently, Bhamra and Uppal (2009) provide a theoretical framework whereby the introduction of a non-redundant derivative causes an increase in the volatility of the spot market.

Empirically, much of 0DTE trading is done by retail traders. Bryzgalova et al. (2023) find that retail investors are now the largest investors in options trading, and their proportion exceeds 60% of the total options trading between November 2019 and June 2021. Consistent with Bryzgalova et al. (2023), an article released by the New York Stock Exchange in 2023 documents that retail investors account for 45% of the options market. Particularly, their trading is more pronounced in short-term expiration options. In 0DTE options trading, retail traders account for 51% of the trading volume, whereas for options with 1-3 months until expiration, their trading volume represents 34%.[2]

Retail traders are typically thought of as noise traders who are speculative and uninformed (Lakonishok et al. 2007; Liu et al. 2020). They attribute to the distortion of stock prices and the heightened level of price volatility (Kumar and Lee 2006; Shleifer and Summers 1990; Shleifer and Vishny 1997). For example, De Long et al. (1990) argue that the unpredictability of noise traders' beliefs can generate risk in the prices and prevent rational arbitrageurs from actively trading against them, leading to an extremely high volatility of stock prices. Barberis, Shleifer, and Wurgler (2005) provide a theoretical framework where different classes of assets can display co-movement because their prices deviate from their fundamental values under the existence of noise traders. Kumar and Lee (2006) reinforce the argument of Barberis, Shleifer, and Wurgler (2005) by providing empirical evidence that retail investors' sentiment can influence prices, resulting in prices deviating from their fundamental values. In line with this idea, more recently, Bloomfield,

[2] Trends in options trading (2023): https://www.nyse.com/data-insights/trends-in-options-trading

O'Hara, and Saar (2009) argue that uninformed traders disturb the process of incorporating new information into prices.

Based on the theoretical literature and participation statistics, we study how 0DTE options trading affects volatility. We conjecture that 0DTE options are a conduit for noise trading. Retail investors constitute the majority of options trading, with their trading volume exceeding 50%, particularly in 0DTE options (Bryzgalova et al. 2023; Poser 2023). And retail investors are commonly regarded as uninformed or noise traders in financial markets (Lakonishok et al. 2007; Liu et al. 2020), injecting noise into security prices and causing deviations from their fundamental value. This noise can contribute to increased volatility (De Long et al. 1990). When retail investors engage in options trading, this noise can influence options prices, which may influence the price process in the underlying asset (Ross 1989).

Consistent with the theory, we show that an increase in 0DTE options trading leads to higher volatility.[3] Using historical 0DTE option volume to overcome endogeneity issues, we document that a one standard deviation increase in 0DTE options volume raises volatility by 24.5%. The effect of 0DTE options trading on volatility is economically much larger than the impact of general options on volatility. Moreover, we show that higher 0DTE options trading worsens market efficiency.

Until recently, trading on 0DTE options linked to the S&P 500 index was not particularly popular. For instance, as recently as January 2011, the monthly 0DTE options trading volume was only 80,000 contracts. This was less than 1% of the monthly options trading volume in the S&P 500 index linked options trading volume. The introduction of SPXW has given investors more frequent 0DTE options trading opportunities. The SPXW contracts allow investors to invest with S&P500 index options with a shorter range of maturities spanning from one week to one month. Starting from the introduction of Friday expiration SPXW in December 2010, investors could access 0DTE options linked to the S&P 500 index at least once a week.[4] Since then, Monday, Tuesday, and Wednesday expiration options have been listed in the market, and lastly, with the introduction of

[3] For brevity, we use the term "*volatility*" to mean the daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes between 9:30 AM and 4:00 PM Eastern Time.
[4] https://ibkr.info/node/1456

Thursday expiration options in May 2022, investors have been able to trade 0DTE options every business day.[5]

The time series evolution of 0DTE options trading linked to the S&P500 index is presented in Figure 1.

[Insert Figure 1 here]

Figure 1 shows a trend of daily 0DTE options trading volume as a percentage of the total trading volume for the S&P500 linked options, denoted by 0DTE%. On the last Friday of January 2011, the daily 0DTE trading volume was 4.31% of the total S&P500 linked options trading volume. But, on the last Friday of December 2022, it was 43.55% of the total options trading volume.

Before testing the relationship between 0DTE and volatility, we first document what drives 0DTE options trading. Following the literature (Engle and Rangel 2008; Paye 2012; Baker et al. 2016), we consider macro- and index-related variables that may affect 0DTE options trading. We find several economically important drivers. Spread variables, such as the term spread and default spread, display a negative relationship with 0DTE options trading. On the other hand, the volatility of the foreign exchange rates and that of the Consumer Price Index (CPI) also show a positive relationship with 0DTE options trading. Moreover, the volatility of the S&P500 index in the previous month exhibits a positive relationship with 0DTE options trading.

We next consider the relationship between 0DTE options trading and volatility. We begin with a simple ordinary least square (OLS) regression and regress volatility on the percent of options volume that is 0DTE. We use the daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes between 9:30 AM and 4:00 PM Eastern Time as the main

[5] Monday-expiration option: https://ir.cboe.com/news/news-details/2016/CBOE-to-List-SPX-Monday-Expiring-Weeklys-Options-07-11-2016/default.aspx,
Wednesday-expiration option: https://ir.cboe.com/news/news-details/2016/CBOE-to-List-SPX-Wednesday-Expiring-Weeklys-Options-02-01-2016/default.aspx,
Tuesday- and Thursday-expiration option: https://ir.cboe.com/news/news-details/2022/Cboe-to-Add-Tuesday-and-Thursday-Expirations-for-SPX-Weeklys-Options-04-13-2022/default.aspx

dependent variable. 0DTE% is the independent variable of interest and captures the percent of options trading in products that expire that day. 0DTE% is defined as the proportion of 0DTE options trade volume over the total trade volume of the S&P500 linked option on a given day. We find a positive association between 0DTE options trading and volatility. A one standard deviation increase in 0DTE% is associated with an approximately 9.03% increase in the volatility.

There are endogeneity concerns with understanding the effect of 0DTE on volatility. Both reverse causality and omitted variable bias may contaminate the OLS regression results. In terms of reverse causality, higher volatility could attract more investors to trade 0DTE options. Moreover, an omitted variable can cause the coefficient estimates to be biased and inconsistent. News or events, such as major economic announcements that affect both 0DTE trading and volatility, could be an omitted factor from the model. For example, a release of FOMC's beige book or the Consumer Price Index (CPI) announcement could lead to increased trading activity in 0DTE options for investors to leverage the information provided in these announcements, resulting in higher volatility (Veronesi 1999; Nofsinger et al. 2003).

To overcome endogeneity concerns, we employ an instrumental variables (IV) approach. We instrument time *t*'s 0DTE% with the 0DTE% from fifty business days ago. A successful IV must satisfy the relevance condition and the exclusion restriction. If these two criteria are met, the IV estimation can provide consistent and unbiased estimates of the parameter of interest. We argue that the 50-lagged 0DTE% is an ideal IV as it satisfies both criteria. First, it satisfies the relevance condition as we show that the 50-lagged 0DTE% is positively associated with the time *t*'s 0DTE%. The first stage of IV regression shows the instrument is statistically significant, as evidenced by the substantial Cragg-Donald F-statistics of 215.4. It, therefore, passes the weak instrument test.

It is not feasible to show the exclusion restriction is satisfied. However, we are able to provide suggestive evidence that this is the case. The exclusion restriction here means that the 50-lagged 0DTE% does not impact volatility except through its relation with the time *t*'s 0DTE%. First, because the 50-lagged 0DTE options expire on that day, it is not possible for the expired options to affect volatility two months in the future. Second, we show that volatility does not display a statistically significant autocorrelation with its own value 50 business days away. As such, while the 50-lagged 0DTE% does predict future variation in 0DTE%, it does not predict future volatility.

Hence, the IV approach allows us to obtain consistent estimates of the causal impact of 0DTE options trading on volatility. Third, we also show that the VIX, a forward-looking measure of stock market volatility, does not statistically significantly forecast volatility 50 business days into the future. Finally, the IV results are robust to using longer lags of 0DTE% as an instrument.

Using this IV design, we regress the volatility on the instrumented 0DTE%. The results are statistically and economically significant. It implies that 0DTE options trading has a significant positive impact on the volatility. The economic magnitude is large but reasonable: one standard deviation in the instrumented 0DTE% increases volatility by 24.51%.

As previously discussed, there is extant literature already showing a link between options trading and volatility. For example, Harris (1989) studies the general relationship between options trading and volatility. He shows the introduction of futures and options products on the S&P 500 in 1983 increased volatility. What we find is that the role of 0DTE options trading on volatility is substantially stronger. The economic magnitude of the effect of 0DTE on volatility is 3.5 times greater than the general options trading effect on volatility.

As 0DTE% has increased over time, we investigate whether the time series is stationary. Both the Augmented Dickey-Fuller test and the Phillips-Perron test statistically reject the null hypothesis that 0DTE% is non-stationary.

A high volatility does not necessarily mean worse market quality. A market that more quickly adapts information or that is experiencing higher flows of information would also have high volatility. It could be that 0DTE% is high when there is more information, which leads to high volatility. To distinguish whether higher volatility is capturing more information or more noise, we consider two price efficiency measures: the variance ratio (VR) and the Hasbrouck (1993) pricing error. We repeat the IV approach with these price efficiency dependent variables and find that 0DTE options trading leads to worse price efficiency. The results confirm that increased 0DTE options trading harms market efficiency.

We conduct a variety of tests to further refine the impact of 0DTE options trading on volatility. First, we consider whether 0DTE differs from other short-horizon options trading. We find that 0DTE has the most pronounced relationship with volatility. Second, we test different volatility frequencies and find that the results are economically similar regardless of the volatility frequency. Third, we analyze intraday variations and show that the impact of 0DTE% on volatility is economically the same in the morning and the afternoon. Finally, we conduct subsample tests and show that since the 2016 introduction of Monday expirations, the 0DTE% - volatility relationship has strengthened.

This paper contributes to the extant literature on options trading and its effect on underlying assets. The literature is quite mixed. Several papers document that options trading decreases volatility in the underlying asset (Conrad 1989; Skinner 1989; Ni et al. 2021). Others find an increase in volatility of the underlying asset (Day and Lewis 1988; Harris 1989; Ni, Pan, and Poteshman 2008; Ni et al. 2021). Finally, a subset of the literature shows no relationship (Kamara, Miller, and Siegel 1992; Long, Schinski, and Officer 1994; Darrat and Rahman 1995; Muravyev, Pearson, and Broussard 2013).

For the effect of options trading on price efficiency, there are also mixed findings. Several studies document that options trading leads to better market quality and pricing efficiency (Kumar et al. 1998; Cao 1999; Cao and Ou-Yang 2008; Roll, Schwartz, and Subrahmanyam 2009; Blanco and Wehrheim 2017). More generally, several studies document that options trading volumes are informative about future stock prices by providing additional information in the market across various settings (Figlewski and Webb 1993; Easley, O'Hara, and Srinivas 1998; Chakravarty, Gulen, and Mayhew 2004; Pan and Poteshman 2006; Hu 2014; Bai, Philippon, and Savov 2016). However, a handful of papers find the opposite, that options trading harms information and efficiency (Chiras and Manaster 1978; Galai 1978; Day and Lewis 1988; Froot et al. 1992; Ni, Pearson, and Poteshman 2005).

While there is extant literature exploring the relationship between options trading and underlying assets, the time-to-expiration dimension has been unexamined. This paper shows that the options trading – volatility relationship depends partly on the type of options traded. We show that the rise of 0DTE options trading is leading to higher volatility and worse price efficiency.

## 2. Data and Variables

In this section, we introduce the data sources and describe the construction of the variables we use. We provide detailed information on these variables' summary statistics. Finally, we conduct an analysis to explore the determinants of Zero-Day-to-Expiration (0DTE) trading volume.

### A. Main Variables

We mainly utilize the Trade and Quote (TAQ) and OptionMetrics databases to examine the impact of 0DTE options trading on volatility. We use the daily volatility as our main dependent variable ($\sigma$). To calculate the volatility measure, we utilize SPY's quote prices from the TAQ database from January 2011 to December 2022. Specifically, we select the midpoint between the bid and ask quote prices every 5 minutes between 9:30 AM and 4:00 PM, resulting in a total of 78 midpoint observations per day. In cases where there is no quote during a given period, we use the midpoint of the previous period to ensure the continuity of the series. Using the midpoint prices, we calculate the 5-minute return and compute the standard deviation of the returns over each trading day to obtain the volatility. This procedure helps the volatility measure capture the intraday price fluctuations while adjusting for the effect of a period with no quote.

The main independent variable in this study, 0DTE%, is derived from OptionMetrics data for the period spanning from January 2011 to December 2022. 0DTE% is defined as:

$$0DTE\%_t = \frac{S\&P500\ linked\ 0DTE\ options\ trading\ volume_t}{Total\ trade\ volume\ of\ S\&P500\ index\ linked\ options_t}. \tag{1}$$

$0DTE\%_t$ measures the proportion of 0DTE options volume traded on a given day relative to the total number of S&P500 index linked options traded on a given day.

When counting the number of days to expiration, we exclude weekends and holidays. For example, when an expiration date falls on a Monday, the trading on the previous Friday is counted as 1DTE to be consistent with the perspective of an investor.

## B. Summary Statistics and Control Variables

We present the descriptive statistics for the main dependent variable ($\sigma_t$) independent variable ($0DTE\%_t$), and control variables in Panel A of Table 1. We provide the detailed definition and calculation of all variables in Table A1. $\sigma_t$ is in basis points (bps). The mean value of $\sigma_t$ is 7.65 bps with a standard deviation of 5.48 bps. When annualized, the average is 10.73% with a corresponding standard deviation of 7.68%. The average $0DTE\%_t$ is 9.10%, and the standard deviation is 12.90% during the sample period. There is a strong increasing trend for $0DTE\%_t$ over the sample, with more recent $0DTE\%_t$ values exceeding 40%. We document the time series of $0DTE\%_t$ in Figure 1. $0DTE\%_t$ was less than 5% until 2016. Panel B of Table 1 shows the correlation between the variables. All correlations are relatively low, with the largest magnitude being 0.52 between $EPU_t$ and $\sigma_t^{1\,Month}$. The correlation table suggests that multicollinearity is not a significant concern.

[Insert Table 1 here]

## C. What Drives 0DTE%?

As little is known about what drives 0DTE options trading activity, we first analyze its determinants. As we focus on the S&P500 index linked short-term expiration options, we consider macroeconomic and index-level variables as determinants. For macroeconomic variables, we include the term spread, the default spread, the volatility of foreign exchange, the volatility of inflation, and the economic and political uncertainty (EPU) measure introduced by Baker et al. (2016). Since these variables are associated with market-level risk and uncertainty, they may impact 0DTE%. Paye (2012) argues that the term spread and default spread can be highly associated with the business cycles and investors' uncertainty on fundamentals. For example, the default spreads respond aggressively at the beginning of economic crises or recessions while it reflects the investor's forecast of future stock volatility. Engle and Rangel (2008) suggest that exchange rates and inflation are important factors in evaluating the future uncertainty in the aggregate economy. Baker et al. (2016) measure of EPU captures the movement of policy-related economic uncertainty. In the analysis, we divide EPU by 100 to make the coefficient comparable. With respect to index-level variables, we choose the volatility of the S&P500 index in the previous month and the S&P500 index return because they are associated with the prices of S&P 500 index options.

To examine the determinants of 0DTE options trading, we regress 0DTE% on the macroeconomic and index-level independent variables. We report the standardized linear regression results, where the variables are scaled by their standard deviations (e.g., Brogaard and Detzel 2015). The interpretation of the estimated coefficients is that one standard deviation change in an independent variable is associated with a beta-standard-deviation change in the dependent variable.

The estimated equation is:

$$0DTE\%_t = \alpha + \beta X_t + \gamma_t + \varepsilon_t, \tag{2}$$

where $0DTE\%_t$ is computed as described in Equation (1), $X_t$ is a vector of independent variables, and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation (HAC) by Newey-West (1994) with optimal lag selection or clustered at the month. Both dependent and independent variables are standardized.

Table 2 presents the determinants of 0DTE options trading. We provide four distinct outcomes, each reflecting a combination of including or excluding days of week fixed effect and employing two different standard error adjustment methods: heteroskedasticity and autocorrelation consistent (HAC) standard error by Newey-West (1994) and clustered standard error at the month level. Regardless of these two combinations, the results are consistent across all specifications. Therefore, we adopt the inclusion of fixed effects and the utilization of the HAC standard errors as the standard approach for the remainder of the paper. The results with clustered standard error at the month level are provided in Table A2.

We find that the determinants account for around 48% of the variation in 0DTE options trading when including the fixed effect, which is presented in columns (2) and (4). With respect to macroeconomic variables, overall, we find that all spread variables have a negative relationship with 0DTE%. It implies wider spreads are associated with lower 0DTE options trading. Additionally, 0DTE options trading is more responsive to the term spread than the default spread. The volatility of the foreign exchange rates and inflation also have a positive relationship with 0DTE%. However, EPU has an insignificant relationship with 0DTE%. Regarding index-level variables, we find that the volatility of the S&P500 index in the previous month exhibits a positive relationship with 0DTE%. Higher realized volatility is associated with a higher 0DTE options trading. The index return does not show a significant relationship with 0DTE%. It is interesting that the overall evidence suggests the increase in macro-related volatility contributes to the increase in 0DTE options trading.

[Insert Table 2 here]

## 3. Does 0DTE Options Trading Increase Volatility?

In this section, we test whether 0DTE options trading increases volatility. We first present the empirical results from an ordinary least squares regression. To overcome endogeneity issues, we implement an instrumental variables (IV) approach. Finally, we test whether price efficiency is harmed when trading more 0DTE options. We find that 0DTE options trading leads to higher volatility and worse price efficiency.

### A. Relation between 0DTE Options Trading and Volatility

We start examining the relationship between 0DTE options trading and volatility by documenting its contemporaneous movements. We regress $Ln(\sigma_t)$ on $0DTE\%_t$ and control variables that correspond to the same given day. We use the logarithm value of $\sigma_t$ in the following regressions to allow a more intuitive interpretation of the log-linear relationship.[6]

The estimated equation is:

$$Ln(\sigma_t) = \alpha + \beta\, 0DTE\%_t + \delta' X_t + \gamma_t + \varepsilon_t, \tag{3}$$

where $Ln(\sigma_t)$ is the log-transformed daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes, $0DTE\%_t$ is the 0DTE% options trading at time $t$, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation by Newey-West (1994) with optimal lag selection.

We include control variables that may affect both volatility and 0DTE options trading to avoid potential issues related to omitted variable bias. To this end, following Paye (2012), we include the spread between the long-term yield on government bonds and short-term Treasury bill rate and the spread between corporate and government bond returns as macroeconomic controls. Drawing on the work of Engle and Rangel (2008), we incorporate inflation and foreign exchange rate volatility to reflect the global macroeconomic environment that would affect our dependent and independent variables. We also include a proxy for the economic policy uncertainty index introduced by Baker et al. (2016) to capture the potential impact of policy uncertainty on volatility and 0DTE options trading. Additionally, we include the volatility of the S&P 500 index in the previous month and the daily return of the index as market-level control variables. Table A1 provides a comprehensive summary of the definition and construction methods of these variables and all variables used in the paper.

Table 3 reports the results of the regression. Column (1) in Table 3 is a simple univariate regression and reveals a positive and statistically significant relationship between 0DTE% and volatility, with

[6] Regardless of taking log on the dependent variable, the results provided thereafter are consistent.

a coefficient of 0.011 significant at the 1% level.[7] Thus, a one standard deviation increase in 0DTE% is associated with a 14.19% increase in volatility.

Furthermore, the inclusion of control variables in the regression models strengthens the robustness of these findings. Column (2) is a regression with macro-related control variables such as spread variables, the volatility of foreign exchange, CPI, and EPU. The result aligns with column (1) that shows a positive and significant relation between 0DTE% and volatility. The result in column (3), with a full set of control variables that additionally include index-related variables, indicates that the positive and significant relationship between 0DTE% and volatility persists.[8] The estimated coefficient is 0.007 and significant at a 1% level. It indicates that a one percentage point increase in 0DTE% is associated with an increase in the volatility by 0.7%. Given that the standard deviation of 0DTE% is 12.90 (in percentage), and the coefficient of 0DTE% is 0.007, the result shows that a one standard deviation increase in 0DTE% is associated with an approximately 9.03% increase in the volatility.[9]

[Insert Table 3 here]

### B. Effect of 0DTE Options Trading on Volatility

There is a potential endogeneity issue that could contaminate the interpretation of the OLS results. The endogeneity problem arises from the possibility of reverse causality between the 0DTE options trading and volatility. Changes in volatility could affect 0DTE%. For example, higher

[7] To mitigate heteroskedasticity and autocorrelation in the volatility and 0DTE options trading at different times, we provide results with alternative clustered standard errors in Panel A of Table A2. We cluster the standard errors at the year level in columns (1) and (2), and at the month level in columns (3) and (4), respectively. The results are robust across alternative clustering choices.

[8] Additionally, we perform an analysis whereby all control variables are lagged by one period, replacing $X_t$ with $X_{t-1}$ in equation (3). The results are economically consistent with the specification using contemporaneous control variables. The estimated coefficient on 0DTE% is 0.005 and is statistically significant at the 1% level.

[9] The economic magnitude of 9.03% is calculated as the multiplication of estimated coefficient of 0DTE% (0.007) and one standard deviation of 0DTE% (12.90), multiplied 100 to express it in percentage. Mathematically, 9.03% = (0.007 x 12.90) x 100.

volatility might lead investors to trade more with 0DTE options. The reverse causality concern may also arise in the presence of autocorrelation of volatility (Ding, Granger, and Engle 1993; Bollerslev and Mikkelsen 1996; Paye 2012). Time *t*'s volatility is influenced by past volatility values, which can create an endogeneity issue. The OLS results can also be contaminated by omitted variables that may affect both the trading activity of 0DTE options and volatility. For example, the release of the FOMC's beige book or CPI announcement may lead to a surge in trading activity in 0DTE options as investors leverage the information from these announcements. These announcements also affect volatility (Veronesi 1999; Nofsinger et al. 2003).

To address the endogeneity issues, we adopt an IV regression approach. The IV approach helps alleviate the issue of reverse causality and omitted variable bias (Wooldridge 2010), so it enables us to attain reliable estimates of the causal influence of 0DTE options trading on volatility. A valid instrument must satisfy the exogeneity and relevance conditions. We use 0DTE% from fifty business days ago as the instrument that satisfies those conditions.

With respect to the exogeneity condition, the lagged 0DTE% cannot correlate with the volatility but through its relation with the time *t*'s 0DTE%. Since the 0DTE options expire on the trading day, the expired options do not directly affect volatility in the following weeks. Moreover, we show that the time *t*'s volatility is not statistically significantly correlated with its own value from 50 business days ago. Figure 2 displays the autocorrelations of volatility measure, $\sigma_t$, where the red vertical dotted line in the middle indicates the 50th lag of $\sigma_t$. The gray shaded area is Bartlett (1978)'s formula for the Moving Average of order q (MA(q)) 95% confidence bands. Bartlett's confidence band suggests that if the estimated autocorrelation falls outside the shaded region, it is statistically different than zero. Since the estimated autocorrelation of the 50th lag falls within the shaded region, it implies that the time *t*'s volatility has no statistically significant correlations with its past volatility from 50 business days ago.

[Insert Figure 2 here]

As such, while the lagged 0DTE% predicts 0DTE% in time *t*, it does not predict the volatility in time *t*.[10]

In terms of the relevance condition, we examine the Cragg-Donald F-statistic from the first stage of the IV regression that explains the power of IV as well as the coefficient on the $0DTE\%_{t-50}$ variable. The estimated equation for the first-stage regression is:

$$0DTE\%_t = \alpha + \beta\ 0DTE\%_{t-50} + \delta' X_t + \gamma_t + u_t, \tag{4}$$

where $0DTE\%_t$ is the 0DTE% options trading at time $t$, $0DTE\%_{t-50}$ is the 0DTE% from 50 business days ago, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation by Newey-West (1994) with optimal lag selection.

We find that the IV is statistically significant, supported by the substantial Cragg-Donald F-statistics of 215.4 when we incorporate all control variables in equation (4).[11] Furthermore, as we will discuss in detail below, the significant coefficient from the first stage regression shows that our instrument is related to the main independent variable, 0DTE%. It captures the trading activity of 0DTE options in the recent past and is correlated with 0DTE% in the current period. Using the valid IV, we estimate the instrumented 0DTE% by regressing the independent variable, 0DTE%, on the IV, fifty business days lagged 0DTE% in the first stage of IV regression. After getting the

[10] To further support the use of 0DTE% as a valid instrument, in Section 3.C we document that alternative measures of volatility, specifically the CBOE volatility index (VIX) and the volatility of the S&P 500 index for a rolling one-month time period from 50 business days ago, also do not predict the time t's volatility.

[11] Cragg-Donald F-statistic is proposed by Cragg and Donald (1993) to evaluate the overall strength of the instruments in the first-stage regression. We choose Cragg-Donald F-statistics because it is more appropriate to test weakness of instrument when dealing with multiple endogenous variables (Stock and Yogo 2005).

instrumented 0DTE%, we regress the volatility on the instrumented 0DTE% in the second stage of IV regression.

The estimated equation for the second stage regression is:

$$Ln(\sigma_t) = \alpha + \beta \ 0\widehat{DTE}\%_t + \delta' X_t + \gamma_t + \varepsilon_t, \tag{5}$$

where $Ln(\sigma_t)$ is the log-transformed daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes, $0\widehat{DTE}\%_t$ is the instrumented 0DTE% from the first-stage regression, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation by Newey-West (1994) with optimal lag selection.

Table 4 presents the results of the IV regressions. Columns (1) to (3) report the results of various specifications of the first stage IV regressions. The findings reveal that the IV satisfies the relevance of the instrument assumption, as evidenced by the statistically significant coefficients regardless of the inclusion of control variables. For example, column (1) shows the results from a simple univariate regression in equation (4). The estimated coefficient of IV is 0.570 and significant at a 1% level.

Next, we include several control variables in regressions, and the finding is consistent that 0DTE% at time *t* is highly correlated with 0DTE% fifty business days ago. In column (2), we include macro-related variables. Even after controlling macroeconomic factors, the result is still significant. The coefficient is 0.254 and significant at a 1% level. Column (3) shows the results from regression with full specification in equation (4). The coefficient is 0.237 and is still significant at a 1% level. It implies that the 0DTE% exhibits a high degree of inertia and remains relatively unchanged over the time horizon. The validity of the IV is supported also by the Cragg-Donald F-statistic in the results. Our IV has a Cragg-Donald F-statistic of 215.4 when incorporating all relevant control variables. The F-statistic is higher than the Stock and Yogo (2005) 10% threshold of 16.38, implying that the instrument is sufficiently strong.

Columns (4) to (6) in Table 4 report the results of the second stage of IV regressions. As the instrumented 0DTE% ($0\widehat{DTE}\%_t$) in the second-stage regression, we employ the estimate in column (3) obtained from the first-stage regression with all relevant control variables.[12] The results show that, regardless of control variable sets, there is a statistically significant and positive relationship between the estimated 0DTE% and volatility at a 1% level.[13] For instance, column (4) shows the result of univariate regression in equation (5). The estimated coefficient is 0.015, and it is statistically significant at a 1% level. Column (5), which includes macro-related control variables, also shows that the instrumented 0DTE% positively affects volatility at a 1% level. Moreover, in column (6), which incorporates all relevant control variables, including index-related variables, the coefficient is 0.019 and statistically significant at the 1% level. The results show that a one standard deviation increase in 0DTE% causes a 24.51% increase in volatility.[14] The results suggest that an increase in 0DTE options trading leads to increased volatility.[15]

Our results align with the findings in several prior studies that options trading results in an increase in volatility. Day and Lewis (1988) document that the option prices are positively associated with the volatility of the underlying stocks, specifically around both quarterly and non-quarterly expiration dates. Harris (1989) finds that the volatility of S&P500 index is heightened after the introduction of futures and options products on S&P500 index. Also, Ni, Pan, and Poteshman (2008) show that the non-market makers' demand for volatility in the option market is positively related to the subsequent realized volatility of underlying stocks. In this regard, our paper

[12] The results obtained from different instrumented 0DTE% measures, using alternative specifications with different control variable sets in the first-stage regression, consistently align with our findings.

[13] To mitigate heteroskedasticity and autocorrelation in the volatility and 0DTE options trading at different times, we provide results with alternative clustered standard errors in Panel B of Table A2. We cluster the standard errors at the year level in columns (1) and (2), and at the month level in columns (3) and (4), respectively. The results are robust across alternative clustering choices.

[14] The economic magnitude of 24.51% is calculated as the multiplication of estimated coefficient of 0DTE% (0.019) and one standard deviation of 0DTE% (12.90), multiplied by 100 to express it in percentage. Mathematically, 24.51% = (0.019 x 12.90) x 100.

[15] We also examine the case where all control variables are lagged one period by replacing $X_t$ with $X_{t-1}$ in equations (4) and (5). The results are economically consistent with the analysis using contemporaneous control variables. The estimated coefficient is 0.012 and is statistically significant at a 1% level along with control variables.

reinforces the results of previous literature that options trading leads to an increased volatility of underlying assets. Additionally, our paper supplements this literature by particularly focusing on short-horizon options trading and showing that 0DTE options trading increases volatility.

Our findings are distinct from those of previous literature in that these indicate a significantly stronger impact of options trading on volatility than what other studies find. Particularly, Harris (1989) examines the effect of the introduction of futures and options products on the S&P500 index in 1983. He finds that the introduction leads to a 7% increase in the volatility of the S&P500 index. The economic impact of 0DTE% on volatility is 3.50 times larger compared to the introduction of futures and options products.[16]

[Insert Table 4 here]

### C. Validation Tests

There are two concerns with regard to the econometric specification used in equation (5) that require further evaluation. First, whether 0DTE% is stationary. Second, whether there the dependent variable exhibits autocorrelation.

Non-stationary independent variables can lead to spurious regression results, suggesting a relationship between variables even when there is none. Figure 1 shows an increasing trend in daily 0DTE% from January 2011 onwards, raising doubts about whether it is stationarity. However, Until mid-2016, SPXW options only provided Friday expiration products, so the 0DTE% values from Monday to Thursday were zero, helping to alleviate concerns about non-stationarity. From May 2022 onwards, SPXW options have expirations every business day, resulting in no zero 0DTE% days.

[16] Except for Harris (1989), it is unclear to fairly compare the magnitude of the positive impact of options trading on underlying assets.

We follow the literature and statistically test for stationarity in 0DTE% using the Augmented Dickey-Fuller test and Phillips-Perron test (e.g., Plazzi, Torous, and Valkanov 2010; Golez and Koudijs 2018; Chen, Joslin, and Ni 2019; Huang and Kilic 2019; Ranaldo, Schaffner, and Vasios 2021). Both test results reject the presence of a unit root at the 1% significance level, implying that 0DTE% is stationary. The test statistic of the Augmented Dickey-Fuller test and Phillips-Perron test for our variable are -34.99 and -44.63, respectively, below the critical value at the 1% level for both tests.[17] The results confirm the stationarity of the 0DTE% variable.

A second potential concern is autocorrelation in volatility. Past volatility may predict time *t*'s volatility as it is well documented that stock return volatility is persistent (Poterba and Summers 1986; French, Schwert, and Stambaugh 1987; Schwert 1989). Hence, the instrument we use is lagged 50 business days. Although we demonstrate in Figure 2 that the 50th-lagged value of volatility does not exhibit a statistically significant autocorrelation with time *t*'s volatility, it is at the statistical threshold, which could still raise concerns about the autocorrelation problem. We, therefore, conduct two additional tests to show that our instrument likely does not violate the exclusion restriction through the autocorrelation of volatility.

First, we consider two alternative volatility proxy measures, the 50-day lagged VIX index and the 50-day lagged realized volatility, to examine whether alternative measures of volatility can forecast volatility 50 days in the future. If these alternative volatility measures can predict future volatility, it would undermine our argument that the 50th-lagged volatility does not influence time *t*'s volatility.

Table 5 presents regression results using time *t*'s volatility as the dependent variable and the 50th-lagged VIX index or realized volatility as the independent variable at *t*-50, along with the same control variables we have been using. Column (1) uses the 50-day lagged VIX index and shows a statistically insignificant coefficient of -0.040. Similarly, column (2) uses the 50-day lagged realized volatility and shows a statistically insignificant coefficient of -0.501. In column (3), we include both volatility variables in the same regression, and the results are also not statistically

[17] The critical values at 10%, 5%, and 1% levels are -2.57, -2.86, and -3.43, respectively, for both tests.

different from zero.[18] These results support the main conclusion that the 50-day lagged volatility measure does not exhibit a statistically significant relationship with time *t*'s volatility.

[Insert Table 5 here]

Second, we consider whether longer lags alter the findings. There is a trade-off. With a longer lag interval, the link between past 0DTE% and current 0DTE% will be weaker. However, the longer lag interval should also reduce the impact of any autocorrelation in volatility. As shown in Figure 2, the 75th and 100th lagged volatilities show no statistically significant autocorrelation with time *t*'s volatility. We repeat the analysis from Table 4 but use the 75th (100th) lagged value of 0DTE% as the IV instead of the 50th lag value.

Table A3 shows the results, and they are consistent with the case when we use 50th lagged values of 0DTE% as our IV. Panel A of Table A3 shows the results when the 75th lagged 0DTE% is used as IV; Panel B of Table A3 shows the results when the 100th lagged 0DTE% is IV.

Panel A shows a statistically significant and positive relationship between the estimated 0DTE% and volatility at a 1% level. Specifically, in column (6) of Panel A, the result indicates that a one standard deviation increase in 0DTE% causes a 16.77% increase in volatility. Similarly, in Panel B, we find a statistically significant and positive relationship between the estimated 0DTE% and volatility persists. In column (6) of Panel B, the result reports that a one standard deviation increase in 0DTE% causes a 14.19% increase in volatility. We conclude that the findings are robust to the change of IV, further alleviating concerns arising due to autocorrelation in volatility.

**D. Effect of 0DTE Options Trading on Price Efficiency**

[18] The results are consistent when using logarithm value of dependent and independent variables.

This section examines whether 0DTE options trading is harmful to the price efficiency of the market. Increased volatility led by increased 0DTE options trading would mean either better or worse price efficiency. If increased volatility is driven by quickly adapting information of 0DTE options trading, the high volatility may indicate improved price efficiency. However, if 0DTE options trading leads to increased volatility due to retail investors who are characterized by their noise trading or speculative investment behaviors, as suggested by theoretical predictions, it is likely to undermine price efficiency. Such traders may introduce more noise into the market, leading to less informative prices and lower price efficiency in the market (Chiras and Manaster 1978). Hence, based on our theoretical prediction, we hypothesize that the increase in 0DTE options trading is detrimental to the price efficiency of the market. We test this hypothesis through a Variance Ratio (VR) test and Hasbrouck's pricing error tests.

To investigate how 0DTE trading affects price efficiency, we first employ the VR test used widely in the literature (e.g., Lo and MacKinlay 1988 and O'Hara and Ye 2011), which is a methodology to measure the degree of price efficiency. The VR test allows us to examine whether the movement of stock prices follows a random walk, implying that stock prices are efficient.

The VR is defined as,

$$VR_t^{(q)} = \frac{Var(r_{t,t-q})}{Var(r_t) * q}, \tag{6}$$

where the variance of $q$-period returns is divided by $q$ times the variance of the single-period returns in the same window. If the asset prices are informationally efficient and generated by a random walk, then the variance of $q$-period returns must be $q$ times as large as the variance of single-period returns. In this case, the VR should be equal to 1. For a more intuitive interpretation, we define the absolute value of VR as,

$$AbsVarRatio_t^{(q)} = \left| VR_t^{(q)} - 1 \right|, \tag{7}$$

where the absolute value of VR is subtracted from one. If $AbsVarRatio_t^{(q)}$ is equal to zero, it implies that the asset prices follow a random walk. On the other hand, if $AbsVarRatio_t^{(q)}$ has a non-negative value, it implies evidence of price inefficiency. The magnitude of the non-negative value implies how large the price inefficiency is.

Previous works have followed this approach by modifying the research design to fit into their models. For example, Boehmer and Kelley (2009) use intraday returns and consider intraday horizons such as (5, 30), (5, 60), (10, 30), and (10, 60) minutes in a daily window to measure price inefficiency. For example, "(5, 30) minutes" means the VR value as the variance of 30-minute returns divided by six times of the variance of the 5-minute returns in a given day. They also consider longer horizons such as (1, 5), (1, 10), and (1, 20) days in the quarterly window. In addition, Ben-David et al. (2018) use a five-day return for the choice of $q$ in the quarterly window. They estimate the absolute value of VR and regress it on their explanatory variable to examine the impact of ETF ownership on price efficiency. They find that ETF ownership leads to the deviation of stock prices from a random walk, implying the deterioration of stock price efficiency. Brogaard, Ringgenberg, and Sovich (2019) use a $q$-day overlapping horizon such as (1, 2), (1, 4), (1, 6), and (1, 8) days in the monthly window. They show their prediction that financialization worsens informativeness is consistent across different horizons. Overall, these methods allow them to show whether their main interest variables lead the asset prices to diverge from a random walk, implying price inefficiency.

Considering these empirical designs for the VR test, we mainly focus on a one-day time window since the frequency of our main variables is at the intraday level. Specifically, in a one-day window, we use pairs of the ratios of (5, 90), (5, 120), (10, 90), and (10, 120) minutes in the spirit of Boehmer and Kelley (2009). We use $q$-period overlapping horizon and adopt the absolute value of VR minus one as our dependent variable ($AbsVarRatio_t^{(q)}$). We then regress $AbsVarRatio_t^{(q)}$ on 0DTE%.

The estimated equation is:

$$AbsVarRatio_t^{(q)} = \alpha + \beta Q_t + \delta' X_t + \gamma_t + \varepsilon_t, \tag{8}$$

where $AbsVarRatio_t^{(q)}$ is defined as the absolute value of $VR_t^{(q)}$ minus 1 in a daily window using a $q$-periods overlapping horizon, and $Q_t$ takes one of our main independent variables: $0DTE\%_t$ or $0\widehat{DTE}\%_t$, which is the first-stage estimate from equation (5). $X_t$ is a vector of control variables and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation by Newey-West (1994) with optimal lag selection.

The VR is adjusted by using an unbiased and efficient estimator of each variance following Lo and MacKinlay (1988). Lo and MacKinaly (1988) devise this estimator to overcome the limited sample size and to improve the power of the VR test. Both dependent and independent variables are standardized. Based on the previous theoretical literature's models that options trading is detrimental to price efficiency (Stein 1987; Froot et al. 1992), we anticipate that 0DTE% is positively associated with $AbsVarRatio_t^{(q)}$. This is because retail investor's noise trading or speculative behaviors on the 0DTE options trading could destabilize the price efficiency.

Panel A in Table 6 reports the results from OLS estimation. The estimated coefficients of 0DTE% are positively associated with each $AbsVarRatio_t^{(q)}$, and most of the coefficients are statistically significant at the 1% level. For example, column (2) shows the results in the cases where we use a pair of ratios of (5, 120) minutes. The result shows that the absolute value of VR minus one is statistically different from 0. It implies the increase in 0DTE options trading causes prices to be inefficient. Columns (3) and (4) show consistent results. They report the results in cases where using pairs of the ratios of (10, 90) and (10, 120) minutes. The estimated coefficient is smaller than when we use a pair of the ratios of (5, 90) and (5, 120) minutes.

The findings from IV estimation are presented in Panel B in Table 6. The results align with those in Panel A for each pair of ratios. These results support our hypothesis that 0DTE options trading deteriorates market price efficiency. The results in Panel B indicate more pronounced price inefficiency from 0DTE options trading. For instance, using a pair of (5, 90) and (5, 120) minutes, the estimated coefficients in columns (1) and (2) are 0.204 and 0.225, which are larger than those in Panel A. The cases using a pair of (10, 90) and (10, 120) minutes presented in columns (3) and

(4) show the consistent result. Overall, the results suggest that $AbsVarRatio_t^{(q)}$ increases with 0DTE%, implying that 0DTE options trading leads to lower price efficiency of the market.

[Insert Table 6 here]

We next employ a different approach, which is Hasbrouck's (1993) pricing error, to examine the association between 0DTE options trading and the price efficiency of the market. Hasbrouck (1993) proposes a model where the observed transaction price can be broken down into two components: an efficient price and a pricing error. The efficient price represents the expected value of a security based on all available information at the time of the transaction. It is assumed for the stock price to follow a random walk and only change when new information becomes available. In contrast, the pricing error accounts for deviations between the observed and efficient prices, which captures various market frictions unrelated to information. The pricing error is characterized as it has a constant mean, and its properties do not change over time (i.e., zero-mean covariance-stationary process). Since the expected value of the pricing errors is zero, the standard deviation of the pricing error denoted as $V(s)_t$, serves as a measure to assess the extent of deviations from the efficient price. We posit that 0DTE% is positively associated with the standard deviation of the pricing error, $V(s)_t$, if 0DTE options trading reduces the price efficiency of the market.

In the empirical estimation, we employ the methodology suggested by Hasbrouck (1993) and Boehmer and Wu (2013) to calculate the standard deviation of the price error within a daily window. We compute a daily price error using second-by-second data from the TAQ, where the trade direction is determined by Lee and Ready (1991) algorithm. To allow a more straightforward interpretation of price error, we utilize the logarithm value of $\sigma_t^{HB}$ denoted as $Ln(\sigma_t^{HB})$.

The estimated equation is:

$$Y = \alpha + \beta Q_t + \delta' X_t + \gamma_t + \varepsilon_t, \tag{9}$$

where $Y$ takes one of our main dependent variables: Hasbrouck's pricing error at $t$ or $t$+1, $Ln(\sigma_t^{HB})$ and $Ln(\sigma_{t+1}^{HB})$, respectively. $Q_t$ takes one of our main independent variables: $0DTE\%_t$ or $0\widehat{DTE}\%_t$, which is an instrumented $0DTE\%_t$ estimated from equation (5). $X_t$ is a vector of control variables and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation by Newey-West (1994) with optimal lag selection.

In Table 7, we document results from both contemporaneous and lagged models following Boehmer and Wu (2013). Boehmer and Wu (2013) employ the lagged model to mitigate the concern that the change in price efficiency measure may be correlated with the contemporaneous independent variables to avoid the endogeneity problem, while they show that the results are robust to using the contemporaneous model.

Table 7 reports that 0DTE options trading positively affects price inefficiency measures in all specifications, implying 0DTE options trading reduces the market price efficiency. Panel A reports the results of OLS estimation, while Panel B reports the results of IV estimation. Columns (1) and (2) report the results from the contemporaneous model, which uses $Ln(\sigma_t^{HB})$ as a price inefficiency measure. Specifically, column (1) of Panel A shows that the estimated coefficient is 0.003, and it is interpreted that a one percent point increase of 0DTE% is associated with the 0.3% decrease in price efficiency. Column (2) of Panel A, which includes the index level of control variables altogether, shows that the estimated coefficient is 0.003, indicating that a one percent point increase in 0DTE% is associated with a 0.3% decrease in price inefficiency as well. Similarly, in IV regression, column (1) of Panel B, which includes only the macroeconomic level of control variables, shows that the estimated coefficient is 0.012, implying that when 0DTE% increases by one percent point, the price efficiency decreases by 1.2%. Column (2) of Panel B, which includes the index level of control variables along with other control variables, shows that the estimated coefficient is 0.008. It is interpreted that a one percent point increase in 0DTE% reduces price efficiency by 0.8%. Economically, if 0DTE% increases by one standard deviation, price efficiency is reduced by approximately 10.32%.[19]

[19] The economic magnitude of 10.32% is calculated as the multiplication of estimated coefficient of 0DTE% (0.008) and one standard deviation of 0DTE% (12.90), multiplied by 100 to express it in percentage. Mathematically, 10.32% = (0.008 x 12.90) x 100.

In columns (3) and (4) of Panel A, the results from the lagged model of OLS regression are provided, and they align with the results from the contemporaneous model. These results suggest that an increase in 0DTE options trading is associated with the reduction of price efficiency the following day. For example, column (3) of Panel A, which includes only the macroeconomic level of control variables, reports that the estimated coefficient is 0.004. It indicates that a one percent point increase in 0DTE% is associated with a 0.4% decrease in price inefficiency. Column (4) of Panel A, which includes the index level of control variables altogether, reports that the estimated coefficient is 0.004, indicating that a one percent point increase of 0DTE% is associated with the 0.4% decrease in price efficiency. Consistent with this, the results from the lagged model of IV regression are provided in columns (3) and (4) of Panel B. These results imply that an increase in 0DTE options trading reduces price efficiency the following day. Specifically, column (3) of Panel B, which includes the macroeconomic level of control variables, shows that the estimated coefficient is 0.012, meaning that price efficiency decreases by 1.2% when 0DTE% increases by one percent point. Column (4) of Panel B, which additionally includes the index level of control variables, also shows that the estimated coefficient is 0.008, implying that when 0DTE% increases by one percent point, the price efficiency decreases by 0.8%. It is economically interpreted that if 0DTE% increases by one standard deviation, price efficiency is reduced by 10.32%.[20] Therefore, the empirical test using Hasbrouck's (1993) pricing error approach reinforces our hypothesis that an increase in 0DTE options trading deteriorates the price efficiency of the market.

Our result is consistent with the evidence found in several previous literature that options trading destabilizes price informativeness and is detrimental to price efficiency. Galai (1978) documents that the trading strategy using options closer to their maturity is strongly related to price inefficiency. Day and Lewis (1988) show that the information transmitted from options trading around its expiration dates is positively associated with the unanticipated parts of underlying asset's volatility, indicating the price inefficiency of underlying assets. Ni, Pearson, and Poteshman (2005) provide evidence that the clustering behavior in the delta-hedge rebalancing or stock price manipulation by investors destabilizes the prices of underlying stocks. Our results

[20] The economic magnitude of 10.32% is calculated as the multiplication of estimated coefficient of 0DTE% (0.008) and one standard deviation of 0DTE% (12.90), multiplied by 100 to express it in percentage. Mathematically, 10.32% = (0.008 x 12.90) x 100.

contribute to this body of research in that we confirm the negative impact of options trading on price efficiency and in that we particularly study a new dimension of options, the short-horizon options trading.

[Insert Table 7 here]

# 4. Robustness

In this section, we present several robustness tests. We identify whether the obtained results are specific to 0DTE or if they also apply to other short-term expiration options, *n*DTEs. Moreover, we use alternative measures of volatility to test our hypothesis. Additionally, we explore whether the effect of 0DTE trading on volatility differs between morning and afternoon trading sessions. Lastly, we conduct subsample tests.

**A. 0DTE versus Non-0DTE**

Thus far, we have shown that 0DTE options trading increases volatility. Since 0DTE options trading impacts volatility, other short-term date expiration options, such as 1DTE or 2DTE options, may also have a similar impact. However, we hypothesize that 0DTE options exhibit the strongest explanation power for volatility not only because of the large volume of retail investors in 0DTE options (Poser 2023) but also because of the unique characteristics of 0DTE options, such as no overnight risk and the expiration occurring on the trading day. These characteristics are proper for speculative investment because they allow investors to realize profit or loss quickly. Given the findings that speculative investors tend to avoid overnight risk (Boes et al. 2007; Bauer et al. 2009; Kelly and Clark 2011; Lou et al. 2019), they would prefer 0DTE over other short-term expiration options. Accordingly, we anticipate that retail investors, who are characterized by their noise trading and speculative behaviors (Lakonishok et al. 2007; Liu et al. 2020), prefer 0DTE to other short-term expiration options, so 0DTE options trading has a stronger impact on volatility than other short-term options trading.

We compare the impact of short-term expiration options on volatility to test our hypothesis statistically by estimating the following regressions:

$$0DTE\%_t = \alpha_1 1DTE\%_t + \alpha_2 2DTE\%_t + \alpha_3 3DTE\%_t + \alpha_4 4DTE\%_t + \epsilon_{0DTE,t}, \tag{10}$$

$$1DTE\%_t = \alpha_1 0DTE\%_t + \alpha_2 2DTE\%_t + \alpha_3 3DTE\%_t + \alpha_4 4DTE\%_t + \epsilon_{1DTE,t}, \tag{11}$$

$$2DTE\%_t = \alpha_1 0DTE\%_t + \alpha_2 1DTE\%_t + \alpha_3 3DTE\%_t + \alpha_4 4DTE\%_t + \epsilon_{2DTE,t}, \tag{12}$$

$$3DTE\%_t = \alpha_1 0DTE\%_t + \alpha_2 1DTE\%_t + \alpha_3 2DTE\%_t + \alpha_4 4DTE\%_t + \epsilon_{3DTE,t}, \tag{13}$$

$$4DTE\%_t = \alpha_1 0DTE\%_t + \alpha_2 1DTE\%_t + \alpha_3 2DTE\%_t + \alpha_4 3DTE\%_t + \epsilon_{4DTE,t}, \tag{14}$$

where *n*DTE denotes the ratio of the trading volume of *n*DTE options over the total trading volume of the S&P500 index linked options and $n$ = 0, 1, …, 4.

We consider the short-term expiration options ranging from 0DTE to 4DTE, which account for one cycle of five business days in a given week. When comparing the impact of the short-term expiration options, we should be careful about identifying a single effect of each *n*DTE, since short-term expiration options with different expiration dates would be traded simultaneously. For example, 0DTE, 1DTE, and 2DTE options are likely to be traded on the same day.

To address the concern, we regress $0DTE\%_t$ on other $nDTE\%_t$ and obtain the residual, $\epsilon_{0DTE,t}$. The residual is the pure variation of 0DTE options, which is not explained by other short-term expiration options. In the same way, we calculate each residual (e.g., $\epsilon_{1DTE,t}$, $\epsilon_{2DTE,t}$, $\epsilon_{3DTE,t}$, and $\epsilon_{4DTE,t}$). Then, we regress volatility on each residual with control variables.

The estimated equation is:

$$Ln(\sigma_t) = \alpha + \beta\, \epsilon_{nDTE,t} + \delta' X_t + \gamma_t + \xi_t, \tag{15}$$

where $Ln(\sigma_t)$ is the log-transformed daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes, $\epsilon_{nDTE,t}$ is the residual of regression of $nDTE\%_t$ on $\sum_{k\neq n} kDTE\%_t$, where $n, k$ = 0, 1, …, 4. $X_t$ is a vector of control variables and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation by Newey-West (1994) with optimal lag selection.

Additionally, we regress volatility on all residuals together with control variables to determine which short-term expiration option accounts for volatility the most in the horse-race style approach as suggested in equation (16):

$$Ln(\sigma_t) = \alpha + \Sigma_{\mathrm{n}=0}^{4}\beta_n\epsilon_{nDTE,t} + \delta' X_t + \gamma_t + \xi_t, \tag{16}$$

where $Ln(\sigma_t)$ is the log-transformed daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes and $\epsilon_{nDTE,t}$ is the residual of regression of $nDTE\%_t$ on $\sum_{k\neq n} kDTE\%_t$, where $n, k$ = 0, 1, …, 4. $X_t$ is a vector of control variables and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation by Newey-West (1994) with optimal lag selection.

From columns (1) to (5) in Table 8, we present the coefficients of the pure variation of other short-term expiration options. Consistent with our baseline results in the previous section, the coefficient of pure variation of 0DTE, $\epsilon_{0DTE,t}$, is 0.008 and exhibits a positive relationship with volatility at the 1% level.[21] Although the estimated coefficient of $\epsilon_{1DTE,t}$ and $\epsilon_{3DTE,t}$ are 0.004 and also show a positive and significant relationship with volatility, the coefficient of $\epsilon_{0DTE,t}$ displays the largest magnitude among others. The pure variation for 2DTE and 4DTE shows an insignificant relation with volatility.

[21] To mitigate heteroskedasticity and autocorrelation in the volatility and 0DTE options trading at different times, we provide results with alternative clustered standard errors in Panel C of Table A2. We cluster the standard errors at the year level in columns (1) and (2), and at the month level in columns (3) and (4), respectively. The results are robust across alternative clustering choices.

Additionally, we provide the result of the horse-race test with all pure variations at the same time in column (6). The result documents that the pure variation of 0DTE, which is not explained by other short-term expiration options, has the largest impact on the volatility, among others. The coefficient of the pure variation of 0DTE is 0.009, surpassing those of other short-term expiration options. Specifically, the coefficients of the pure variation of 1DTE and 2DTE are 0.006 and 0.003. Additionally, the coefficient of the pure variation of 3DTE is not significantly related to the volatility, while that of 4DTE has a negative relation with the volatility.

[Insert Table 8 here]

**B. Alternative Volatility Measures**

We assess the robustness of our findings by using alternative volatility measures. We replace the volatility with the volatility at 10- and 30-minute frequency returns and regress them on $0\widehat{DTE}\%_t$ following the equation (5). In Table 9, we display the results of the IV regression using those volatilities at different frequencies as dependent variables. Irrespective of the volatility measures used, our results consistently demonstrate that 0DTE options trading has a positive and statistically significant impact on volatility. For each one percentage point increase in 0DTE%, the 10- and 30-minute volatilities are estimated to increase by 2% and 2.3%, respectively. It should be noted that the coefficients obtained in Table 9 are naturally larger compared to our main results. It is attributed to the use of lower frequency volatility measures in this analysis.

[Insert Table 9 here]

**C. Morning and Afternoon Volatility**

We next investigate and compare the influence of 0DTE options trading on the morning and afternoon volatility. This analysis is motivated by the trading data that 0DTE option investors trade the options more in the morning than in the afternoon. OptionAlpha, which is one of the options trading platforms, issued a report that analyzed 0DTE option traders' trading behavior. Using 0DTE options trading data in 2022, they find that the most widely used strategies for 0DTE investors are "Iron Butterfly" and "Iron Condor." The report shows that 0DTE option traders typically open these two strategies within the first two hours of the trading day.[22] Based on the Option's Alpha's reports, there are more 0DTE options trading in the morning than in the afternoon, therefore, we predict a larger impact.

In this empirical analysis, we expect that investors are more likely to trade 0DTE options in the morning, resulting in a higher impact on volatility in the morning than in the afternoon.

To test our hypothesis statistically, we regress the morning and afternoon volatility on 0DTE%. However, it should be noted that this regression can introduce look-ahead bias unless the timing of variables is adjusted. The morning volatility only considers the trading activity in the morning, while the 0DTE% variable includes both morning and afternoon 0DTE options trading activities. It means that 0DTE% can contain information on the afternoon trading that is unavailable when calculating the morning volatility. It can lead to a biased estimate of the relationship between morning volatility and 0DTE%, which could affect the validity of the results. To avoid this bias, and since the lagged 0DTE% and 0DTE% at time *t* are highly correlated, we regress the morning and afternoon volatilities on the one business day lagged instrumented 0DTE%.

The estimated equation is:

$$Y_{t+1} = \alpha + \beta\, 0\widehat{DTE}\%_t + \delta' X_t + \gamma_t + \varepsilon_t, \tag{17}$$

where $Y_{t+1}$ takes one of our main dependent variables: Morning $Ln(\sigma_{t+1})$ or Afternoon $Ln(\sigma_{t+1})$. Morning (Afternoon) $Ln(\sigma_{t+1})$ is the logarithm value of the daily standard deviation of the SPDR S&P 500 ETF's midpoint quote return every 5 minutes between 9:30 AM and 12:00 PM (12:00

[22] https://optionalpha.com/blog/0dte-options-strategy-performance, and https://optionalpha.com/blog/0dte

PM and 4:00 PM) Eastern Time at $t$+1. $0\widehat{DTE}\%_t$ is the first-stage estimate from equation (5), $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. All standard errors are adjusted for heteroskedasticity and autocorrelation by Newey-West (1994) with optimal lag selection.

Table 10 presents the impact of 0DTE options trading on the morning volatility and the afternoon volatility. The magnitude of the impact of 0DTE options trading on the morning volatility is economically similar to that on the afternoon volatility. In column (1), the coefficient representing the sensitivity of morning volatility to 0DTE options trading is 0.020, while in column (2), the coefficient representing the sensitivity of afternoon volatility to 0DTE options trading is 0.019. The findings reveal that when 0DTE% increases by a one percentage point, the morning and afternoon volatilities increase by 2.00% and 1.90%, respectively. These results suggest that the impact of 0DTE options trading on the morning and afternoon volatility are economically similar and reject our hypothesis that more 0DTE options trading in the morning leads to a higher impact on volatility in the morning than in the afternoon.

[Insert Table 10 here]

**D. Subsample Tests**

As seen in Figure 1, the proportion of the trading volume of 0DTE options over the total trading volume for the S&P500 linked options has increased since 2016. The introduction of Monday and Wednesday-expiration options in 2016 appears to have contributed to the growth of 0DTE options trading. Based on the graphical evidence, we posit that the impact of 0DTE options trading on volatility became more significant and positive with the introduction of Monday-expiration options in 2016. Before the introduction of Monday-expiration options, there may have been no or minimal impact of 0DTE options trading on volatility, but a significant relationship has emerged since then.

To assess our hypothesis, we divide our sample into two distinct periods - the period before the introduction of the Monday-expiration SPXW option in 2016 (Pre-Mon) and the period from the introduction to the end of 2022 (Post-Mon) - and conduct the IV regressions in equation (4).

Table 11 shows that the results are in line with our initial expectations. As shown in column (1), there is no significant impact of 0DTE options trading on volatility for the period prior to the introduction of Monday-expiration options. Although the coefficient is 0.003, it is not statistically different from zero. However, in column (2), it is evident that 0DTE options trading has a statistically significant and positive effect on volatility after the introduction. In column (2), a one percentage point increase of estimated 0DTE options trading activity results in an increase of 2.2% in the volatility. It can be economically interpreted that a one standard deviation increase in 0DTE% causes a 32.10% increase in volatility after the introduction.[23]

It suggests that the impact of 0DTE options trading on volatility may have changed over time, with a discernible effect emerging after the introduction of new options in 2016. It also implies that the increasing size and volume of 0DTE options trading could potentially harm market stability, leading to heightened volatility.

[Insert Table 11 here]

## 5. Conclusion

In recent years, there has been a significant increase in the trading volume and proportion of Zero-Day-to-Expiration (0DTE) options linked to the S&P500 index. Since these options expire on the same day they are traded, they ensure that investors are not exposed to overnight risk and allow for the rapid realization of profit or loss. These characteristics are preferred by retail investors who

[23] The economic magnitude of 32.10% is calculated as the multiplication of estimated coefficient of 0DTE% (0.022) and one standard deviation of 0DTE% (14.59) during the Post-Mon period (untabulated), multiplied by 100 to express it in percentage. Mathematically, 32.10% = (0.022 x 14.59) x 100.

favor speculative investments that would infuse noise into price. According to an NYSE report in 2023, more than half of the trading volume in 0DTE options trading is attributed to retail investors. The growth of 0DTE option trading, led by retail investors, has raised concerns about the impact of 0DTE options on volatility, potentially leading to a reduction in market efficiency. The absence of prior research regarding the effect of 0DTE options on the financial market has prompted us to investigate the relationship between 0DTE options trading and volatility.

Adopting an instrumental variable (IV) approach to address endogeneity concerns, we examine the causal impact of 0DTE options trading on volatility. We find that an increase in 0DTE options trading results in higher volatility. This finding is consistent with the view that more uninformed or speculative options trading can increase the volatility of the underlying assets by transmitting additional noises in the market.

The higher volatility could arise either when the market quickly incorporates information or when the market captures more noise. We hypothesize that 0DTE options trading is harmful to the price efficiency of the market. This is because if the increased volatility stems from an investor's noise trading or speculative trading behavior, it induces greater noise into the price, potentially destabilizing the price efficiency of the market. Consistent with this conjecture, we find that 0DTE options trading deteriorates the price efficiency of the market by means of the Variance Ratio (VR) and Hasbrouck's pricing error tests.

We further analyze whether the impact of short-term expiration options on volatility is distinctive in 0DTE options trading compared to other short-term expiration options. Because of 0DTE options' speculative trading characteristics, such as no overnight risk and a quick profit or loss realization, noise traders or speculative investors favor 0DTE options trading, and it drives more pronounced results than other short-term expiration options. We find that the impact of 0DTE options trading on volatility is stronger and more significant than that of other short-term expiration options. Additionally, we provide evidence to validate our findings under several settings, such as alternative volatility measures with lower frequency, different horizons, and a breakpoint of the sample period. The results consistently support the primary finding of our study.

This paper contributes to the existing literature on options trading and its impact on underlying assets, which has shown mixed findings. While some studies indicate that options trading decreases volatility in the underlying asset, others suggest an increase or show no relationship. Similarly, with respect to price efficiency, findings in the literature are also mixed. Some studies propose improved market quality and pricing efficiency due to options trading, while others argue the opposite. We provide evidence that the increase in 0DTE options trading leads to higher volatility and reduced price efficiency.

Furthermore, this paper contributes to option literature by examining unexplored dimensions, time-to-expiration. By exploring this new perspective, this paper provides evidence that the relationship between options trading and volatility depends on the type of options traded. In this regard, this paper advances the understanding of the impact of short-term options trading on its underlying assets, in contrast to prior studies that concentrate on the effects of general options trading.

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# Tables and Figures

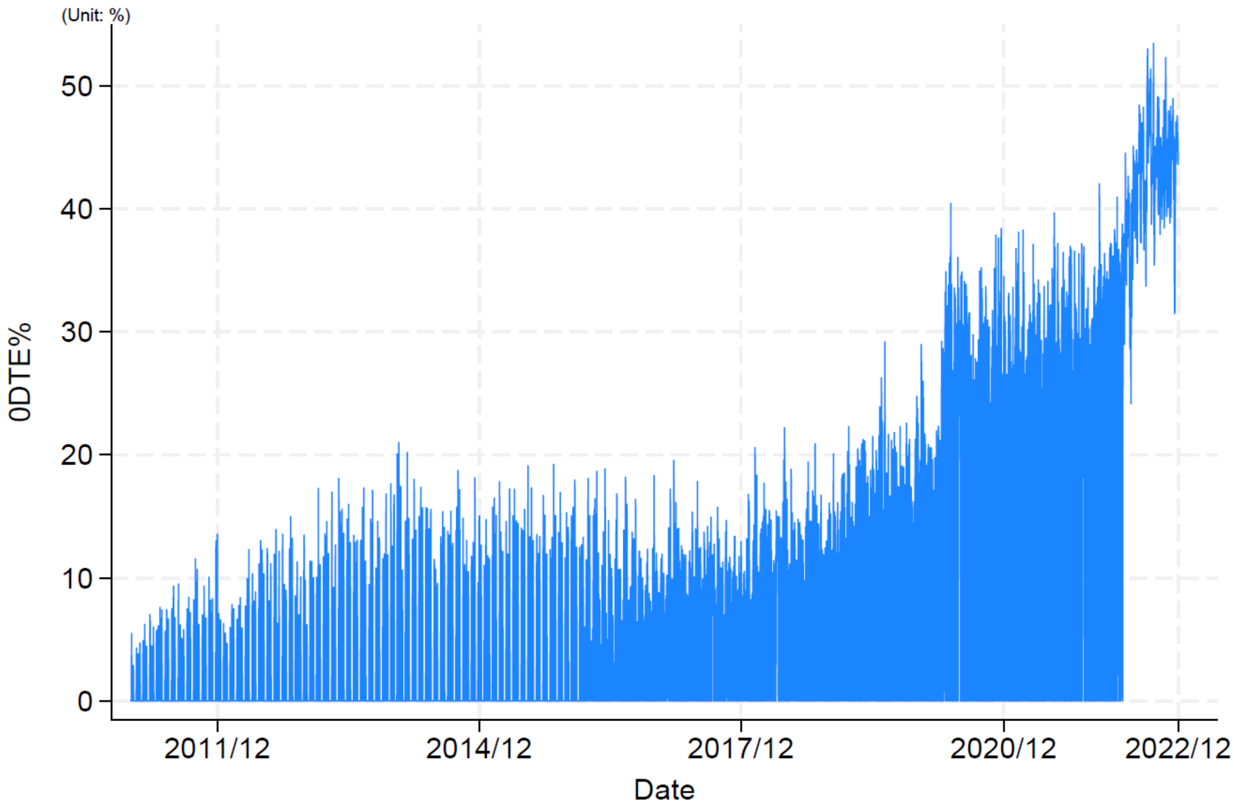
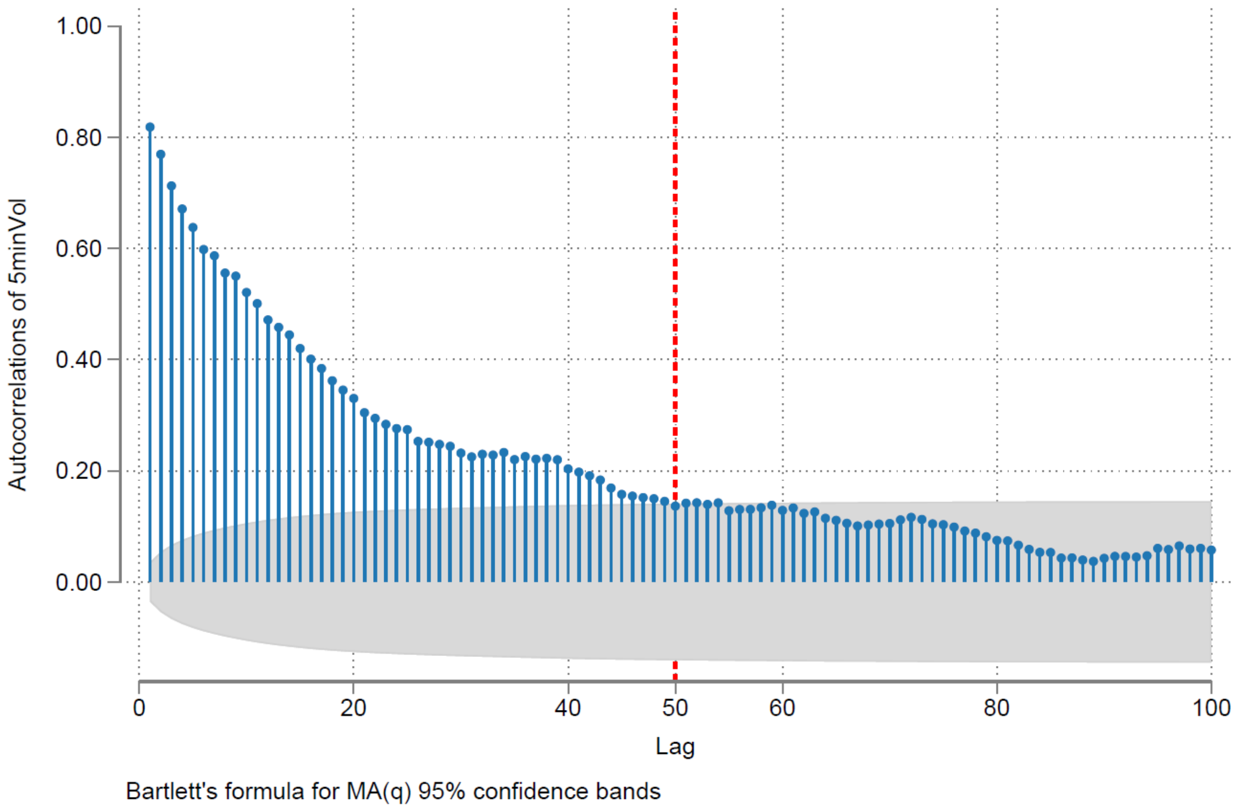



Figure 1: The trend of daily 0DTE%

This figure shows the daily trading volume of 0DTE as a percentage of the total trading volume for the S&P500 linked options (as denoted by 0DTE%) from January 2011 to December 2022.




# Figure 2: The autocorrelations of volatility

This figure shows the autocorrelations of $\sigma_t$, which is a proxy for volatility. The red vertical dotted line at the center indicates the 50th lag of $\sigma_t$. The gray shaded area is Bartlett (1978)'s formula for the Moving Average of order q (MA(q)) 95% confidence bands. Bartlett's confidence band suggests that if the estimated autocorrelation falls outside the shaded region, it is statistically different than zero.

# Table 1: Descriptive Statistics

The table presents descriptive statistics for our main dependent ($\sigma_t$), independent variable (*0DTE%*), and control variables. Details of the variables are stated in Appendix Table A1. Panel A reports descriptive statistics for the variables, and Panel B reports the correlations between the variables. The sample covers from January 2011 to December 2022.

**Panel A: Summary Statistics**

| | (1)<br>N | (2)<br>Mean | (3)<br>Std. Dev. | (4)<br>Min | (5)<br>Median | (6)<br>Max |
|---|---|---|---|---|---|---|
| $\sigma_t$ (bp) | 3,020 | 7.65 | 5.48 | 1.38 | 6.15 | 71.10 |
| Morning $\sigma_t$ (bp) | 3,020 | 8.49 | 5.88 | 1.63 | 6.98 | 74.60 |
| Afternoon $\sigma_t$ (bp) | 3,020 | 6.87 | 5.41 | 1.06 | 5.34 | 69.32 |
| $0DTE\%_t$ (%) | 3,020 | 9.10 | 12.90 | 0.00 | 0.00 | 53.44 |
| $Term\ Spread_t$ (%) | 3,020 | 1.50 | 0.88 | -0.90 | 1.56 | 3.60 |
| $Default\ Spread_t$ (%) | 3,020 | 2.49 | 0.48 | 1.56 | 2.39 | 4.31 |
| $\sigma_t^{forex}$ | 2,997 | 0.30 | 0.11 | 0.10 | 0.28 | 0.87 |
| $\sigma_t^{cpi}$ | 2,995 | 0.62 | 0.41 | 0.19 | 0.47 | 1.94 |
| $EPU_t$ | 2,837 | 1.20 | 0.86 | 0.03 | 0.97 | 8.08 |
| $\sigma_t^{1\ Month}$ | 3,020 | 0.92 | 0.61 | 0.30 | 0.74 | 5.62 |
| $Index\ Return_t$ (%) | 3,020 | 0.04 | 1.12 | -11.59 | 0.06 | 8.67 |

**Panel B: Correlations**

| | (1)<br>$\sigma_t$ | (2)<br>$0DTE\%_t$ | (3)<br>$Term\ Spread_t$ | (4)<br>$Default\ Spread_t$ | (5)<br>$\sigma_t^{forex}$ | (6)<br>$\sigma_t^{gcpi}$ | (7)<br>$EPU_t$ | (8)<br>$\sigma_t^{1\ Month}$ | (9)<br>$Index\ Return_t$ |
|---|---|---|---|---|---|---|---|---|---|
| (1) $\sigma_t$ | 1.00 | | | | | | | | |
| (2) $0DTE\%_t$ | 0.23 | 1.00 | | | | | | | |
| (3) $Term\ Spread_t$ | -0.13 | -0.45 | 1.00 | | | | | | |
| (4) $Default\ Spread_t$ | 0.25 | -0.32 | 0.29 | 1.00 | | | | | |
| (5) $\sigma_t^{forex}$ | 0.33 | 0.13 | 0.00 | 0.41 | 1.00 | | | | |
| (6) $\sigma_t^{cpi}$ | 0.20 | 0.38 | 0.02 | -0.17 | 0.16 | 1.00 | | | |
| (7) $EPU_t$ | 0.35 | 0.19 | -0.20 | 0.26 | 0.27 | 0.14 | 1.00 | | |
| (8) $\sigma_t^{1\ Month}$ | 0.48 | 0.26 | -0.21 | 0.32 | 0.52 | 0.15 | 0.52 | 1.00 | |
| (9) $Index\ Return_t$ | -0.21 | -0.02 | 0.00 | 0.02 | 0.02 | -0.02 | 0.04 | 0.02 | 1.00 |

## Table 2: What Drives 0DTE Options Trading

The table presents evidence about the association between 0DTE% and control variables to identify the main drivers of 0DTE options trading. The regression is

$$0DTE\%_t = \alpha + \beta' X_t + \gamma_t + \varepsilon_t,$$

where $0DTE\%_t$ is computed as the ratio of the total volume of 0DTE options traded over the total trading volume of the S&P500 linked options expressed as a percentage, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. Details of the control variables are stated in Appendix Table A1. Both dependent variables and independent variables are standardized. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. In columns (1) and (2), Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. In columns (3) and (4), the standard errors are clustered at the month level. The sample covers the period from January 2011 to December 2022.

| Dependent variable = | $0DTE\%_t$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Term\ Spread_t$ | -0.329*** | -0.331*** | -0.329*** | -0.331*** |
| | (-4.98) | (-4.99) | (-6.58) | (-6.56) |
| $Default\ Spread_t$ | -0.275*** | -0.271*** | -0.275*** | -0.271*** |
| | (-5.33) | (-5.31) | (-6.89) | (-6.83) |
| $\sigma_t^{forex}$ | 0.092 | 0.089 | 0.092** | 0.089* |
| | (1.59) | (1.53) | (1.98) | (1.89) |
| $\sigma_t^{cpi}$ | 0.300*** | 0.302*** | 0.300*** | 0.302*** |
| | (4.98) | (5.04) | (6.44) | (6.50) |
| $EPU_t$ | 0.044 | 0.024 | 0.044 | 0.024 |
| | (1.01) | (0.55) | (1.21) | (0.64) |
| $\sigma_t^{1\ Month}$ | 0.161** | 0.173** | 0.161** | 0.173** |
| | (2.28) | (2.46) | (2.39) | (2.61) |
| $Index\ Return_t$ | -0.016 | -0.005 | -0.016 | -0.005 |
| | (-1.00) | (-0.38) | (-1.04) | (-0.37) |
| Constant | -0.001 | | -0.001 | |
| | (-0.02) | | (-0.03) | |
| Observations | 2,974 | 2,974 | 2,974 | 2,974 |
| Adjusted R-squared | 0.409 | 0.483 | 0.409 | 0.483 |
| Days of week FE | No | Yes | No | Yes |
| Clustered Standard Errors | No | No | Month | Month |

## Table 3: OLS Analysis of 0DTE Options Trading and Volatility

The table presents the association between 0DTE options trading and volatility. The regression is

$$Ln(\sigma_t) = \alpha + \beta\ 0DTE\%_t + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $Ln(\sigma_t)$ is the logarithm value of the daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes, $0DTE\%_t$ is computed as the ratio of the total volume of 0DTE options traded over the total trading volume of the S&P500 linked options expressed as a percentage, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. Details of the control variables are stated in Appendix Table A1. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

| Dependent variable = | $Ln(\sigma_t)$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $0DTE\%_t$ | 0.011*** | 0.009*** | 0.007*** |
| | (5.17) | (4.37) | (3.95) |
| $Term\ Spread_t$ | | -0.029 | -0.012 |
| | | (-0.92) | (-0.43) |
| $Default\ Spread_t$ | | 0.263*** | 0.205** |
| | | (2.99) | (2.49) |
| $\sigma_t^{forex}$ | | 0.494* | 0.139 |
| | | (1.85) | (0.59) |
| $\sigma_t^{cpi}$ | | 0.123 | 0.114 |
| | | (1.36) | (1.47) |
| $EPU_t$ | | 0.108*** | 0.065** |
| | | (4.02) | (2.10) |
| $\sigma_t^{1\ Month}$ | | | 0.213** |
| | | | (2.40) |
| $Index\ Return_t$ | | | -0.094*** |
| | | | (-9.64) |
| Observations | 3,020 | 2,974 | 2,974 |
| Adjusted R-squared | 0.069 | 0.267 | 0.355 |
| Days of week FE | Yes | Yes | Yes |

## Table 4: IV Analysis of 0DTE Options Trading and Volatility

The table presents a causal impact of 0DTE options trading and volatility using IV regression. The first-stage regression is

$$0DTE\%_t = \alpha + \beta\ 0DTE\%_{t-50} + \delta' X_t + \gamma_t + u_t,$$

where $0DTE\%_t$ is computed as the ratio of the total volume of 0DTE options traded over the total trading volume of the S&P500 linked options expressed as a percentage, $0DTE\%_{t-50}$ is the 0DTE% fifty business days ago, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. The second-stage regression is

$$Ln(\sigma_t) = \alpha + \beta\ 0\widehat{DTE}\%_t + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $Ln(\sigma_t)$ is the logarithm value of the daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes, $0\widehat{DTE}\%_t$ is the estimated 0DTE% from the first-stage regression, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. Columns (1) to (3) report the estimates from the first-stage of IV regression, and columns (4) to (6) report the estimates from the second-stage of IV regression where the dependent variable is the $5minVol_t$, with Cragg-Donald F-statistic following Stock and Yogo (2005). Details of the control variables are stated in Appendix Table A1. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

| Dependent variable = | First-stage estimates $0DTE\%_t$ | | | Second-stage estimates $Ln(\sigma_t)$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $0DTE\%_{t-50}$ | 0.570*** | 0.254*** | 0.237*** | | | |
| | (6.80) | (3.47) | (3.31) | | | |
| $0\widehat{DTE}\%_t$ | | | | 0.015*** | 0.036*** | 0.019*** |
| | | | | (4.82) | (4.67) | (2.91) |
| $Term\ Spread_t$ | | -4.220*** | -3.917*** | | 0.113*** | 0.043 |
| | | (-6.48) | (-6.21) | | (2.68) | (1.16) |
| $Default\ Spread_t$ | | -4.944*** | -5.648*** | | 0.437*** | 0.293*** |
| | | (-4.75) | (-5.18) | | (4.37) | (2.73) |
| $\sigma_t^{forex}$ | | 13.825** | 8.101* | | 0.049 | 0.030 |
| | | (2.45) | (1.66) | | (0.15) | (0.12) |
| $\sigma_t^{cpi}$ | | 7.926*** | 7.720*** | | -0.143 | 0.001 |
| | | (4.93) | (4.96) | | (-1.15) | (0.01) |
| $EPU_t$ | | 0.897* | 0.155 | | 0.075** | 0.060* |
| | | (1.72) | (0.27) | | (2.09) | (1.87) |
| $\sigma_t^{1\ Month}$ | | | 3.114** | | | 0.168* |
| | | | (2.49) | | | (1.86) |
| $Index\ Return_t$ | | | -0.040 | | | -0.093*** |
| | | | (-0.29) | | | (-9.35) |
| Observations | 2,970 | 2,924 | 2,924 | 2,924 | 2,924 | 2,924 |
| Adjusted R-squared | | | | 0.060 | 0.030 | 0.310 |
| Days of week FE | | | | Yes | Yes | Yes |
| Cragg-Donald F-statistic | 393.6 | 110.8 | 215.4 | | | |

# Table 5: Does Past Volatility Predict Current Volatility?

The table presents evidence about the association between time *t*'s volatility and volatility-related variables. The regression is

$$\sigma_t = \alpha + \beta Q_{t-50} + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $\sigma_t$ is the daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes, $Q_{t-50}$ takes either $VIX_{t-50}$ or $\sigma_{t-50}^{Rolling1M}$, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. Details of the control variables are stated in Appendix Table A1. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

| Dependent variable = | $\sigma_t$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $VIX_{t-50}$ | -0.040 | | -0.015 |
| | (-0.65) | | (-0.29) |
| $\sigma_{t-50}^{Rolling1M}$ | | -0.501 | -0.355 |
| | | (-0.73) | (-0.63) |
| $Term\ Spread_t$ | -0.946** | -0.965** | -0.967** |
| | (-2.17) | (-2.38) | (-2.14) |
| $Default\ Spread_t$ | 1.882* | 1.905** | 1.912* |
| | (1.79) | (2.06) | (1.79) |
| $\sigma_t^{forex}$ | 8.693*** | 8.695*** | 8.726*** |
| | (3.04) | (3.27) | (3.03) |
| $\sigma_t^{cpi}$ | 1.652* | 1.569** | 1.613* |
| | (1.88) | (2.04) | (1.82) |
| $EPU_t$ | 1.782*** | 1.752*** | 1.765*** |
| | (3.17) | (3.08) | (3.23) |
| $Index\ Return_t$ | -1.161*** | -1.161*** | -1.161*** |
| | (-7.58) | (-7.18) | (-7.63) |
| Observations | 2,924 | 2,924 | 2,924 |
| Adjusted R-squared | 0.280 | 0.280 | 0.280 |
| Days of week FE | Yes | Yes | Yes |

## Table 6: Price Efficiency: Variance Ratio Test

The table reports the impact of 0DTE options trading on price efficiency using the Variance Ratio (VR) test. The VR is denoted as $VR_t^{(q)}$, which is the ratio of the variance of $q$-period returns divided by $q$ times the variance of one-period return in time window $T$, by using an unbiased estimator following Lo and MacKinlay (1988). The regression is

$$AbsVarRatio_t^{(q)} = \alpha + \beta Q_t + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $AbsVarRatio_t^{(q)}$ is defined as the absolute value of $VR_t^{(q)}$ minus 1 in a daily window using a $q$-periods overlapping horizon, and $Q_t$ takes one of our main independent variables: $0DTE\%_t$ or $0\widehat{DTE\%}_t$, the first-stage estimate from Table 4. $X_t$ is a vector of control variables and $\gamma_t$ is a day of the week fixed effect. Details of the control variables are stated in Appendix Table A1. Panel A reports the results of OLS estimation, and Panel B reports the results of IV estimation. Both dependent variables and independent variables are standardized. We report Cragg-Donald F-statistic following Stock and Yogo (2005). The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

**Panel A: OLS Estimation**

| Dependent variable = | $AbsVarRatio_t^{(q)}$ | | | |
|---|---|---|---|---|
| ($t$, $q$) = | (5,90) | (5,120) | (10,90) | (10,120) |
| | (1) | (2) | (3) | (4) |
| $0DTE\%_t$ | 0.096*** | 0.086** | 0.099*** | 0.075** |
| | (2.70) | (2.50) | (2.77) | (2.08) |
| $Term\ Spread_t$ | 0.012 | 0.003 | 0.007 | -0.003 |
| | (0.58) | (0.15) | (0.34) | (-0.17) |
| $Default\ Spread_t$ | 0.040* | 0.048** | 0.058** | 0.054** |
| | (1.74) | (2.20) | (2.29) | (2.29) |
| $\sigma_t^{forex}$ | -0.023 | -0.011 | -0.027 | -0.013 |
| | (-1.07) | (-0.52) | (-1.24) | (-0.61) |
| $\sigma_t^{cpi}$ | 0.030 | 0.035* | 0.027 | 0.041* |
| | (1.25) | (1.66) | (1.18) | (1.87) |
| $EPU_t$ | -0.042** | -0.045** | -0.039* | -0.036* |
| | (-2.01) | (-2.27) | (-1.72) | (-1.67) |
| $\sigma_t^{1\ Month}$ | -0.024 | -0.020 | -0.018 | -0.014 |
| | (-1.13) | (-0.94) | (-0.73) | (-0.56) |
| $Index\ Return_t$ | 0.074*** | 0.084*** | 0.082*** | 0.088*** |
| | (2.86) | (2.75) | (3.32) | (2.78) |
| Observations | 2,974 | 2,974 | 2,974 | 2,974 |
| Adjusted R-squared | 0.009 | 0.010 | 0.010 | 0.010 |
| Days of week FE | Yes | Yes | Yes | Yes |

## Table 6 Continued.

**Panel B: IV Estimation**

| Dependent variable = | $AbsVarRatio_t^{(q)}$ | | | |
|---|---|---|---|---|
| $(t, q)$ = | (5,90) | (5,120) | (10,90) | (10,120) |
| | (1) | (2) | (3) | (4) |
| $0\widehat{DTE}\%_t$ | 0.204* | 0.225** | 0.219** | 0.221** |
| | (1.92) | (2.27) | (2.28) | (2.23) |
| $Term\ Spread_t$ | 0.049 | 0.051 | 0.050 | 0.050 |
| | (1.27) | (1.39) | (1.33) | (1.43) |
| $Default\ Spread_t$ | 0.069* | 0.085** | 0.089** | 0.092** |
| | (1.96) | (2.47) | (2.41) | (2.44) |
| $\sigma_t^{forex}$ | -0.032 | -0.023 | -0.038* | -0.026 |
| | (-1.40) | (-0.99) | (-1.66) | (-1.15) |
| $\sigma_t^{cpi}$ | -0.003 | -0.007 | -0.010 | -0.005 |
| | (-0.08) | (-0.20) | (-0.27) | (-0.13) |
| $EPU_t$ | -0.044** | -0.049** | -0.042* | -0.039* |
| | (-2.10) | (-2.28) | (-1.76) | (-1.73) |
| $\sigma_t^{1\ Month}$ | -0.042 | -0.044 | -0.038 | -0.039 |
| | (-1.47) | (-1.52) | (-1.14) | (-1.09) |
| $Index\ Return_t$ | 0.074*** | 0.085*** | 0.083*** | 0.089*** |
| | (2.92) | (2.74) | (3.34) | (2.82) |
| Observations | 2,924 | 2,924 | 2,924 | 2,924 |
| Adjusted R-squared | 0.004 | 0.002 | 0.004 | 0.001 |
| Days of week FE | Yes | Yes | Yes | Yes |
| Cragg-Donald F-statistic | 215.4 | 215.4 | 215.4 | 215.4 |

# Table 7: Price Efficiency: Hasbrouck's Pricing Error Test

The table reports the impact of 0DTE options trading on price efficiency using Hasbrouck's (1993) pricing error, which is indicated as $\sigma_t^{HB}$. The regression is

$$Y = \alpha + \beta Q_t + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $Y$ takes one of our main dependent variables: The logarithm value of Hasbrouck's pricing error at $t$ or $t$+1, $Ln(\sigma_t^{HB})$ or $Ln(\sigma_{t+1}^{HB})$, respectively. $Q_t$ takes one of our main independent variables: $0DTE\%_t$ or $0\widehat{DTE}\%_t$, the first-stage estimates from Table 4. $X_t$ is a vector of control variables and $\gamma_t$ is a day of the week fixed effect. Details of the control variables are stated in Appendix Table A1. Panel A reports the results of OLS estimation, and Panel B reports the results of IV estimation. Columns (1) and (2) display the contemporaneous model, while columns (3) and (4) report the lagged model. A day of the week fixed effect is used in columns (2) and (4) from both Panels A and B. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. We report Cragg-Donald F-statistic following Stock and Yogo (2005). Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

**Panel A: OLS Estimation**

| Dependent variable = | $Ln(\sigma_t^{HB})$ | | $Ln(\sigma_{t+1}^{HB})$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $0DTE\%_t$ | 0.003*** | 0.003*** | 0.004*** | 0.004*** |
| | (5.15) | (4.45) | (6.04) | (5.53) |
| $Term\ Spread_t$ | -0.047*** | -0.043*** | -0.043*** | -0.039*** |
| | (-4.24) | (-4.05) | (-3.91) | (-3.67) |
| $Default\ Spread_t$ | 0.017 | 0.002 | 0.024 | 0.010 |
| | (0.54) | (0.07) | (0.77) | (0.33) |
| $\sigma_t^{forex}$ | 0.298*** | 0.201** | 0.251*** | 0.163** |
| | (3.42) | (2.35) | (2.99) | (1.98) |
| $\sigma_t^{cpi}$ | 0.015 | 0.014 | 0.012 | 0.010 |
| | (0.59) | (0.59) | (0.48) | (0.45) |
| $EPU_t$ | 0.049*** | 0.037** | 0.047*** | 0.036** |
| | (3.50) | (2.48) | (3.43) | (2.43) |
| $\sigma_t^{1\ Month}$ | | 0.057*** | | 0.052*** |
| | | (2.82) | | (2.83) |
| $Index\ Return_t$ | | -0.015* | | -0.018*** |
| | | (-1.94) | | (-4.66) |
| Constant | 0.003*** | 0.003*** | 0.004*** | 0.004*** |
| | (5.15) | (4.45) | (6.04) | (5.53) |
| Observations | 2,974 | 2,974 | 2,973 | 2,973 |
| Adjusted R-squared | 0.189 | 0.204 | 0.190 | 0.206 |
| Days of week FE | Yes | Yes | Yes | Yes |

# Table 7: Continued.

**Panel B: IV Estimation**

| Dependent variable = | $Ln(\sigma_t^{HB})$ | | $Ln(\sigma_{t+1}^{HB})$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $0\widehat{DTE}\%_t$ | 0.012*** | 0.008** | 0.012*** | 0.008*** |
| | (3.92) | (2.54) | (4.39) | (3.25) |
| $Term\ Spread_t$ | -0.002 | -0.018 | -0.003 | -0.018 |
| | (-0.12) | (-1.32) | (-0.21) | (-1.37) |
| $Default\ Spread_t$ | 0.070* | 0.038 | 0.071** | 0.040 |
| | (1.83) | (0.88) | (2.05) | (1.07) |
| $\sigma_t^{forex}$ | 0.158* | 0.152* | 0.128 | 0.123 |
| | (1.68) | (1.75) | (1.38) | (1.45) |
| $\sigma_t^{cpi}$ | -0.067 | -0.034 | -0.061 | -0.030 |
| | (-1.59) | (-0.88) | (-1.60) | (-0.90) |
| $EPU_t$ | 0.040*** | 0.036** | 0.039** | 0.035** |
| | (2.71) | (2.43) | (2.52) | (2.34) |
| $\sigma_t^{1\ Month}$ | | 0.038* | | 0.037** |
| | | (1.76) | | (2.10) |
| $Index\ Return_t$ | | -0.015* | | -0.018*** |
| | | (-1.94) | | (-4.35) |
| Observations | 2,924 | 2,924 | 2,923 | 2,923 |
| Adjusted R-squared | 0.097 | 0.169 | 0.118 | 0.182 |
| Days of week FE | Yes | Yes | Yes | Yes |
| Cragg-Donald F-statistic | 110.8 | 215.4 | 110.3 | 214.2 |

## Table 8: 0DTE vs Non-0DTE

The table presents a causal impact of 0DTE% to 4DTE% on volatility. 1DTE% to 4DTE% represents the non-0DTE%. To isolate the pure effect of each *n*DTE%, we regress each *n*DTE% on other short-term expiration options and obtain the residual, $\epsilon_{nDTE_t}$ following the equations (10) to (14). Then, we run the following regression. The regression is

$$Ln(\sigma_t) = \alpha + \beta\ \epsilon_{nDTE,t} + \delta' X_t + \gamma_t + \xi_t,$$

where $Ln(\sigma_t)$ is the logarithm value of the daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes, $\epsilon_{nDTE,t}$ is the estimated residual from equations (10) to (14) as the proxy for the pure variation of *n*DTE% not explained by other short-term expiration options, $X_t$ is a vector of control variables, $\gamma_t$ is a day of the week fixed effect, and $n$ = 0, 1, …, 4. Details of the control variables are stated in Appendix Table A1. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

| Dependent variable = | $Ln(\sigma_t)$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\epsilon_{0DTE,t}$ | 0.008*** | | | | | 0.009*** |
| | (3.97) | | | | | (3.85) |
| $\epsilon_{1DTE,t}$ | | 0.004* | | | | 0.006** |
| | | (1.84) | | | | (2.32) |
| $\epsilon_{2DTE,t}$ | | | 0.002 | | | 0.003** |
| | | | (1.17) | | | (2.04) |
| $\epsilon_{3DTE,t}$ | | | | 0.004** | | -0.000 |
| | | | | (2.43) | | (-0.28) |
| $\epsilon_{4DTE,t}$ | | | | | 0.001 | -0.003** |
| | | | | | (0.53) | (-2.53) |
| $Term\ Spread_t$ | -0.008 | -0.037 | -0.046 | -0.045** | -0.047 | 0.014 |
| | (-0.29) | (-1.27) | (-1.55) | (-2.47) | (-1.59) | (0.46) |
| $Default\ Spread_t$ | 0.212** | 0.169** | 0.154** | 0.156*** | 0.153* | 0.247*** |
| | (2.56) | (2.13) | (1.97) | (3.48) | (1.94) | (2.82) |
| $\sigma_t^{forex}$ | 0.136 | 0.211 | 0.216 | 0.218 | 0.213 | 0.126 |
| | (0.58) | (0.88) | (0.91) | (1.30) | (0.89) | (0.52) |
| $\sigma_t^{cpi}$ | 0.105 | 0.164** | 0.180** | 0.177*** | 0.182** | 0.065 |
| | (1.35) | (2.04) | (2.24) | (3.67) | (2.28) | (0.79) |
| $EPU_t$ | 0.064** | 0.064** | 0.067** | 0.067*** | 0.067** | 0.058* |
| | (2.08) | (2.04) | (2.13) | (2.61) | (2.15) | (1.85) |
| $\sigma_t^{1\ Month}$ | 0.211** | 0.238** | 0.240** | 0.239*** | 0.239** | 0.206** |
| | (2.39) | (2.53) | (2.54) | (4.50) | (2.54) | (2.34) |
| $Index\ Return_t$ | -0.094*** | -0.094*** | -0.094*** | -0.094*** | -0.094*** | -0.093*** |
| | (-9.68) | (-9.76) | (-9.69) | (-10.99) | (-9.66) | (-9.87) |
| Observations | 2,974 | 2,974 | 2,974 | 2,974 | 2,974 | 2,974 |
| Adjusted R-squared | 0.357 | 0.340 | 0.339 | 0.340 | 0.338 | 0.362 |
| Days of week FE | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 9: Robustness: Alternative Volatility Intervals

The table presents a causal impact of 0DTE options trading and volatility, using alternative frequency of volatility measures. The regression is

$$Y_t = \alpha + \beta\, 0\widehat{DTE\%}_t + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $Y_t$ takes one of our main dependent variables: $Ln(\sigma_t^{10min})$ or $Ln(\sigma_t^{30min})$. $Ln(\sigma_t^{10min})$ and $Ln(\sigma_t^{30min})$ are the logarithm values of the daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 10 minutes and 30 minutes, respectively. $0\widehat{DTE\%}_t$ is the first-stage estimate from Table 4, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. Details of the control variables are stated in Appendix Table A1. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. We report Cragg-Donald F-statistic following Stock and Yogo (2005). Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

| Dependent variable = | $Ln(\sigma_t^{10min})$ | $Ln(\sigma_t^{30min})$ |
|---|---|---|
| | (1) | (2) |
| $0\widehat{DTE\%}_t$ | 0.020*** | 0.023*** |
| | (2.98) | (3.10) |
| $Term\ Spread_t$ | 0.045 | 0.050 |
| | (1.15) | (1.22) |
| $Default\ Spread_t$ | 0.315*** | 0.344*** |
| | (2.82) | (2.89) |
| $\sigma_t^{forex}$ | 0.036 | 0.027 |
| | (0.14) | (0.10) |
| $\sigma_t^{cpi}$ | 0.000 | 0.003 |
| | (0.00) | (0.03) |
| $EPU_t$ | 0.060* | 0.061* |
| | (1.76) | (1.72) |
| $\sigma_t^{1\ Month}$ | 0.168* | 0.159 |
| | (1.77) | (1.63) |
| $Index\ Return_t$ | -0.094*** | -0.089*** |
| | (-9.25) | (-8.05) |
| Observations | 2,924 | 2,924 |
| Adjusted R-squared | 0.299 | 0.250 |
| Days of week FE | Yes | Yes |
| Cragg-Donald F-statistic | 215.4 | 215.4 |

# Table 10: Robustness: Morning and Afternoon Volatility

The table presents the impact of 0DTE options trading on the morning and afternoon volatility. The regression is

$$Y_{t+1} = \alpha + \beta\ 0\widehat{DTE\%}_t + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $Y_{t+1}$ takes one of our main dependent variables: Morning $Ln(\sigma_{t+1})$ or Afternoon $Ln(\sigma_{t+1})$. Morning (Afternoon) $Ln(\sigma_{t+1})$ is the logarithm value of the daily standard deviation of the SPDR S&P 500 ETF's midpoint quote return every 5 minutes between 9:30 AM and 12:00 PM (12:00 PM and 4:00 PM) Eastern Time at *t*+1. $0\widehat{DTE\%}_t$ is the first-stage estimate from Table 4, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. Details of the control variables are stated in Appendix Table A1. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. We report Cragg-Donald F-statistic following Stock and Yogo (2005). Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

| Dependent variable = | Morning $Ln(\sigma_{t+1})$ | Afternoon $Ln(\sigma_{t+1})$ |
|---|---|---|
| | (1) | (2) |
| $0\widehat{DTE\%}_t$ | 0.020*** | 0.019** |
| | (3.52) | (2.43) |
| $Term\ Spread_t$ | 0.036 | 0.047 |
| | (0.99) | (1.07) |
| $Default\ Spread_t$ | 0.333*** | 0.313** |
| | (3.94) | (2.30) |
| $\sigma_t^{forex}$ | -0.061 | 0.040 |
| | (-0.28) | (0.13) |
| $\sigma_t^{cpi}$ | 0.047 | 0.017 |
| | (0.59) | (0.16) |
| $EPU_t$ | 0.052* | 0.059* |
| | (1.65) | (1.68) |
| $\sigma_t^{1\ Month}$ | 0.183*** | 0.234** |
| | (2.62) | (2.08) |
| $Index\ Return_t$ | -0.098*** | -0.100*** |
| | (-8.47) | (-8.39) |
| Observations | 2,924 | 2,924 |
| Adjusted R-squared | 0.304 | 0.272 |
| Days of week FE | Yes | Yes |
| Cragg-Donald F-statistic | 215.4 | 215.4 |

## Table 11: Robustness: Subsample Tests

The table presents the impact of 0DTE options trading on volatility by dividing the sample into two periods. The introduction date of the Monday-expiring SPXW, which was August 15, 2016, is set as a breakpoint. The regression is

$$Ln(\sigma_t) = \alpha + \beta\, 0\widehat{DTE\%}_t + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $Ln(\sigma_t)$ is the logarithm value of the daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes, $0\widehat{DTE\%}_t$ is the estimated 0DTE% from the first-stage regression, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. Details of the control variables are stated in Appendix Table A1. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. We report Cragg-Donald F-statistic following Stock and Yogo (2005). Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

| Dependent variable = | $Ln(\sigma_t)$ | |
|---|---|---|
| | (1) | (2) |
| Periods | Pre-Mon | Post-Mon |
| $0\widehat{DTE\%}_t$ | 0.003 | 0.022*** |
| | (0.09) | (2.86) |
| $Term\ Spread_t$ | 0.107** | 0.056 |
| | (1.99) | (0.72) |
| $Default\ Spread_t$ | 0.289*** | 0.294 |
| | (3.04) | (1.47) |
| $\sigma_t^{forex}$ | 0.188 | -0.327 |
| | (0.83) | (-0.62) |
| $\sigma_t^{cpi}$ | 0.099 | -0.080 |
| | (0.72) | (-0.57) |
| $EPU_t$ | 0.097*** | 0.055 |
| | (2.60) | (1.57) |
| $\sigma_t^{1\ Month}$ | 0.227*** | 0.159 |
| | (3.57) | (1.60) |
| $Index\ Return_t$ | -0.089*** | -0.088*** |
| | (-7.74) | (-6.60) |
| Observations | 1,342 | 1,582 |
| Adjusted R-squared | 0.333 | 0.329 |
| Days of week FE | Yes | Yes |
| Cragg-Donald F-statistic | 6.557 | 80.67 |

# Appendix

## Table A1: Variable Definitions

| Symbol | Definition |
|---|---|
| | *The main independent and dependent variables* |
| $\sigma_t$ | The daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes between 9:30 AM and 4:00 PM Eastern Time. |
| $\sigma_t^{10min}$ | The daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 10 minutes between 9:30 AM and 4:00 PM Eastern Time. |
| $\sigma_t^{30min}$ | The daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 30 minutes between 9:30 AM and 4:00 PM Eastern Time. |
| Morning $\sigma_t$ | The daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes between 9:30 AM and 12:00 PM Eastern Time. |
| Afternoon $\sigma_t$ | The daily standard deviation of the SPDR S&P 500 ETF's (SPY) midpoint quote return every 5 minutes between 12:00 PM and 4:00 PM Eastern Time. |
| $VIX_t$ | The daily CBOE volatility index. |
| $nDTE\%_t$ | The ratio of the total volume of $n$DTE (where $n = 1, 2, 3, and$ 4) options traded over the total volume of the S&P500 linked options traded in each day expressed as a percentage. |
| $AbsVarRatio_t^{(q)}$ | The absolute value of Variance Ratio minus 1 in time window *T*, using *q*-periods overlapping horizon. The Variance Ratio is defined as $VR_t^{(q)}$, which is the ratio of the variance of *q*-period returns divided by the variance of one-period return in the time window $T$. We adjust the VR by using an unbiased and efficient estimator of each variance following Lo and MacKinlay (1988). $$AbsVarRatio_t^{(q)} = \left\|VR_t^{(q)} - 1\right\|, \quad VR_t^{(q)} = \frac{Var(r_{t,t-q})}{Var(r_t) * q}$$ |
| $\sigma_t^{HB}$ | The daily standard deviation of the pricing error using second-by-second data from the TAQ following Hasbrouck (1993). |
| $\epsilon_{nDTE,t}$ | The residual of regression of $nDTE\%_t$ on $\sum_{k \neq n} kDTE\%_t$, where $n, k$ = 0, 1, …, 4. For example, $\epsilon_{0DTE,t}$ is the residual of the following regression: $$0DTE\%_t = \alpha_0 + \alpha_1 1DTE\%_t + \alpha_2 2DTE\%_t + \alpha_3 3DTE\%_t + \alpha_4 4DTE\%_t + \epsilon_{0DTE,t}$$ Using fitted value, $$\epsilon_{0DTE,t} = 0DTE\%_t - (\hat{\alpha}_1 1DTE\%_t + \hat{\alpha}_2 2DTE\%_t + \hat{\alpha}_3 3DTE\%_t + \hat{\alpha}_4 4DTE\%_t)$$ |

## Table A1 Continued.

| | |
|---|---|
| | *Control Variables: Macroeconomics level* |
| $Term\ Spread_t$ | The daily difference between the long-term yield on government bonds and the Treasury bill rate. |
| $Default\ Spread_t$ | The daily difference between the yield on BAA-rated corporate bonds and the yield on long-term US government bonds. |
| $\sigma_t^{forex}$ | The standard deviation of the daily return of the foreign exchange rates over the previous 22-day rolling periods. |
| $\sigma_t^{cpi}$ | The standard deviation of the previous 12-month returns based on the year-over-year returns of the Consumer Price Index (CPI). |
| $EPU_t$ | The daily Economic Policy Uncertainty (EPU) index in Baker et al. (2016). |
| | *Control Variables: Index level* |
| $\sigma_t^{1\ Month}$ | The standard deviation of the daily returns of the S&P 500 index in the previous month. |
| $\sigma_t^{Rolling1M}$ | The standard deviation of the daily returns of the S&P 500 index over the previous 22-day rolling periods. |
| $Index\ Return_t$ | The daily return of the S&P 500 index. |

## Table A2: Alternative Robustness for Clustered Standard Errors

The table presents evidence about how the clustering way of standard errors affects the main findings in Tables 3, 4, and 8 with different control variable settings. Panel B only reports the estimates from the second-stage of IV regression from Table 4. Two different standard error clustering ways are used. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample covers the period from January 2011 to December 2022.

| | Panel A: Table 3 | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $0DTE\%_t$ | 0.011** | 0.007*** | 0.011*** | 0.007*** |
| | (2.78) | (3.16) | (6.48) | (4.21) |
| Observations | 3,020 | 2,837 | 3,020 | 2,837 |
| Adjusted R-squared | 0.047 | 0.325 | 0.047 | 0.325 |
| Days of week FE | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes |
| Clustered Standard Errors | Year | Year | Month | Month |
| | Panel B: Table 4 | | | |
| | (1) | (2) | (3) | (4) |
| $0\widehat{DTE}\%_t$ | 0.014** | 0.019 | 0.014*** | 0.019*** |
| | (2.99) | (1.73) | (5.95) | (3.30) |
| Observations | 2,970 | 2,790 | 2,970 | 2,790 |
| Adjusted R-squared | 0.032 | 0.284 | 0.032 | 0.284 |
| Days of week FE | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes |
| Cragg-Donald F-statistic | 1481 | 410.9 | 1481 | 410.9 |
| Clustered Standard Errors | Year | Year | Month | Month |
| | Panel C: Table 8 0DTE vs. Non-0DTEs | | | |
| | (1) | (2) | (3) | (4) |
| $\epsilon_{0DTE,t}$ | 0.010*** | 0.009** | 0.010*** | 0.009*** |
| | (3.29) | (2.79) | (7.20) | (4.16) |
| $\epsilon_{1DTE,t}$ | 0.003 | 0.006* | 0.003 | 0.006** |
| | (0.58) | (1.83) | (1.29) | (2.49) |
| $\epsilon_{2DTE,t}$ | 0.001 | 0.003 | 0.001 | 0.003** |
| | (0.45) | (1.48) | (0.72) | (2.19) |
| $\epsilon_{3DTE,t}$ | -0.003 | -0.000 | -0.003* | -0.000 |
| | (-1.60) | (-0.20) | (-1.85) | (-0.29) |
| $\epsilon_{4DTE,t}$ | -0.004* | -0.003** | -0.004** | -0.003*** |
| | (-1.90) | (-2.54) | (-2.60) | (-2.78) |
| Observations | 3,020 | 2,837 | 3,020 | 2,837 |
| Adjusted R-squared | 0.048 | 0.331 | 0.048 | 0.331 |
| Days of week FE | Yes | Yes | Yes | Yes |
| Controls | No | Yes | No | Yes |
| Clustered Standard Errors | Year | Year | Month | Month |

# Table A3: Alternative Robustness for Instruments with Different Lag of 0DTE%

The table presents a causal impact of 0DTE options trading and volatility using IV regression. The first-stage regression is

$$0DTE\%_t = \alpha + \beta\, Q + \delta' X_t + \gamma_t + u_t,$$

where $0DTE\%_t$ is computed as the ratio of the total volume of 0DTE options traded over the total trading volume of the S&P500 linked options expressed as a percentage, $Q$ takes one of different lagged 0DTE%: $0DTE\%_{t-75}$ or $0DTE\%_{t-100}$, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. The second-stage regression is

$$Ln(\sigma_t) = \alpha + \beta\, 0\widehat{DTE}\%_t + \delta' X_t + \gamma_t + \varepsilon_t,$$

where $Ln(\sigma_t)$ is the logarithm value of 5-minute daily volatility as a standard deviation of midpoints selected from the bid-ask quote prices every 5 minutes between 9:30 AM and 4:00 PM Eastern Time, $0\widehat{DTE}\%_t$ is the estimated 0DTE% from the first-stage regression, $X_t$ is a vector of control variables, and $\gamma_t$ is a day of the week fixed effect. Columns (1) to (3) report the estimates from the first-stage of IV regression, and columns (4) to (6) report the estimates from the second-stage of IV regression where the dependent variable is the $Ln(\sigma_t)$, with Cragg-Donald F-statistic following Stock and Yogo (2005). Details of the control variables are stated in Appendix Table A1. The *t*-statistics are presented in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Newey-West (1994) heteroskedasticity- and autocorrelation-consistent (HAC) *t*-statistics (with optimal lag selection) are reported in parentheses. The sample covers the period from January 2011 to December 2022.

**Panel A: Instrument with 75th lagged 0DTE%**

| Dependent variable = | First-stage estimates $0DTE\%_t$ | | | Second-stage estimates $Ln(\sigma_t)$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $0DTE\%_{t-75}$ | 0.605*** | 0.304*** | 0.290*** | | | |
| | (7.78) | (4.83) | (4.72) | | | |
| $0\widehat{DTE}\%_t$ | | | | 0.015*** | 0.027*** | 0.013*** |
| | | | | (4.84) | (5.16) | (2.88) |
| $Term\ Spread_t$ | | -4.223*** | -3.874*** | 0.065 | 0.010 | -4.223*** |
| | | (-5.56) | (-5.30) | (1.64) | (0.32) | (-5.56) |
| $Default\ Spread_t$ | | -4.518*** | -5.207*** | 0.382*** | 0.249** | -4.518*** |
| | | (-4.69) | (-5.09) | (4.08) | (2.57) | (-4.69) |
| $\sigma_t^{forex}$ | | 13.610** | 7.885 | 0.200 | 0.099 | 13.610** |
| | | (2.42) | (1.63) | (0.66) | (0.40) | (2.42) |
| $\sigma_t^{cpi}$ | | 7.787*** | 7.533*** | -0.057 | 0.061 | 7.787*** |
| | | (4.49) | (4.56) | (-0.54) | (0.76) | (4.49) |
| $EPU_t$ | | 0.750 | 0.032 | 0.084*** | 0.061* | 0.750 |
| | | (1.45) | (0.06) | (2.69) | (1.94) | (1.45) |
| $\sigma_t^{1\ Month}$ | | | 3.065** | | 0.190** | |
| | | | (2.52) | | (2.15) | |
| $Index\ Return_t$ | | | -0.097 | | -0.093*** | |
| | | | (-0.67) | | (-9.49) | |
| Observations | 2,945 | 2,899 | 2,899 | 2,899 | 2,899 | 2,899 |
| Adjusted R-squared | | | | 0.062 | 0.159 | 0.346 |
| Days of week FE | | | | Yes | Yes | Yes |
| Cragg-Donald F-statistic | 416.4 | 146.9 | 324.2 | | | |

# Table A3 Continued.

**Panel B: Instrument with 100th lagged 0DTE%**

| Dependent variable = | First-stage estimates $0DTE\%_t$ | | | Second-stage estimates $Ln(\sigma_t)$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $0DTE\%_{t-100}$ | 0.612*** | 0.300*** | 0.285*** | | | |
| | (7.89) | (5.11) | (4.88) | | | |
| $0\widehat{DTE}\%_t$ | | | | 0.014*** | 0.027*** | 0.011*** |
| | | | | (4.57) | (4.53) | (2.65) |
| $Term\ Spread_t$ | | -4.423*** | -4.088*** | 0.062 | -0.002 | -4.423*** |
| | | (-5.09) | (-4.86) | (1.41) | (-0.07) | (-5.09) |
| $Default\ Spread_t$ | | -4.614*** | -5.297*** | 0.379*** | 0.235** | -4.614*** |
| | | (-4.69) | (-5.07) | (4.12) | (2.51) | (-4.69) |
| $\sigma_t^{forex}$ | | 14.395** | 8.772* | 0.203 | 0.110 | 14.395** |
| | | (2.43) | (1.70) | (0.67) | (0.45) | (2.43) |
| $\sigma_t^{cpi}$ | | 7.879*** | 7.649*** | -0.053 | 0.082 | 7.879*** |
| | | (4.28) | (4.33) | (-0.51) | (1.11) | (4.28) |
| $EPU_t$ | | 0.827 | 0.120 | 0.085*** | 0.061* | 0.827 |
| | | (1.61) | (0.21) | (2.70) | (1.94) | (1.61) |
| $\sigma_t^{1\ Month}$ | | | 2.994** | | 0.200** | |
| | | | (2.39) | | (2.21) | |
| $Index\ Return_t$ | | | -0.045 | | -0.092*** | |
| | | | (-0.32) | | (-9.56) | |
| Observations | 2,920 | 2,874 | 2,874 | 2,874 | 2,874 | 2,874 |
| Adjusted R-squared | | | | 0.063 | 0.166 | 0.354 |
| Days of week FE | | | | Yes | Yes | Yes |
| Cragg-Donald F-statistic | 405 | 136.2 | 295 | | | |