Market Makers and the Dynamics of Volatility Demand

January 6, 2026

Abstract

Investors typically are net long volatility to hedge against market downturns, but paradoxically reduce these positions during high-risk periods. We explain this puzzle by estimating the latent demand curves of market-makers and end-users in the zero-net-supply market for VIX options. During high-risk periods, both demand curves shift right, but the shift in market-maker demand dominates that of end-users. This results in reduced net long positions of end-users, high volatility returns on long positions, and wider bid-ask spreads. Market-makers actively manage inventory and profitability while providing market liquidity, increasing demand when inventory constraints bind and when expected volatility returns are high.

Keywords: Volatility; VIX Options; Intermediaries; Demand Systems; Market Makers; End Users; Latent Demand; Market Turmoil

JEL Classification: G01, G13, G14, G20

1 Introduction

The Chicago Board Options Exchange (CBOE) introduced VIX futures in 2004, followed by VIX options in 2006. Both products have been a resounding success, with rapidly expanding trading volumes.[1] Consistent with a hedging motive, investors have consistently been net long VIX calls (and net short VIX puts) to hedge against spikes in volatility and market downturns.[2] However, the literature on volatility markets has recently highlighted two puzzling stylized facts that occur during high-risk periods (Cheng, 2019, 2020; Atmaz and Buffa, 2023). The first puzzle is that ex-ante estimates of the volatility risk premium fall or stay flat in high-risk periods. The second puzzle, possibly related to the first one, is that investor volatility exposures fall during these high-risk periods and even turn negative during extreme volatility events. The latter stylized fact suggests that investor hedging demand declines when hedging is more beneficial, or alternatively that investor speculation declines in periods when it is potentially more profitable.

While the first puzzle has received substantial attention in the literature that models volatility risk premiums (see, e.g., Atmaz and Buffa 2023; Ghaderi, Kilic, and Seo 2024; Lochstoer and Muir 2022), the puzzling patterns in net demand remain largely unexplored. This paper aims to fill this gap in the literature by analyzing the patterns in equilibrium volatility net demand and their determinants, which play a key role in the volatility market's equilibrium. Specifically, we use the VIX option positions of various market participants constructed from the CBOE Open-Close data to explain the second puzzle. We show that the decline in end users' (i.e., non market makers) net volatility exposure during high-risk periods reflects the equilibrium outcome in a zero-net-supply market, resulting from the intersection of the volatility demand curves of

[1] Growth in trading activity has further accelerated in recent years. From 2015 to 2023, the average daily volume (ADV) of VIX options grew from 570,000 to 740,000 contracts, while the ADV of VIX futures increased from 205,000 to 215,000 contracts. By August 2024, the ADV for VIX options surged to nearly 1.2 million contracts, while VIX futures reached 300,000 contracts.

[2] The strong negative relationship between market returns and changes in implied volatility is well documented. In our sample, the correlation between daily changes in the VIX and S&P 500 returns is approximately −82%.

end users and market makers. We identify these (latent) demand curves from observable (equilibrium) returns and end-user net positions using a structural vector auto-regression with sign restrictions (Faust 1998; Canova and De Nicolo 2002; Uhlig 2005). This demand system approach departs from traditional option pricing models, which typically assume that prices respond only to information about future fundamentals or discount rates and are unaffected by demand shocks. In contrast, our approach explicitly allows prices to depend on quantity and demand shocks. Extracting these latent demands allows us to distinguish between the role of end users and market makers in shaping equilibrium net demand during high-risk periods.

We find that both end-user and market-maker volatility demand shift right in high-risk periods. However, these demand shifts are significantly more pronounced for market makers, resulting in an increase in their net positions and a corresponding decline in end users' positions. Alternatively, we can interpret this demand system as an interaction between the demand of end users and the supply of market makers. From this perspective, the increase in the two demand curves during high-risk periods is equivalent to market makers scaling back supply while end-user demand rises. Market makers, who typically are net short volatility through their short VIX call holdings, reduce supply during high-risk periods to manage inventory and limit their negative exposure to volatility. Market makers make the largest adjustments for short-maturity options, which reflects their aversion to absorbing excessive short-term volatility risk. These adjustments by market makers lead to a decline in net volatility exposure for end users, even though their latent demand curve shifts right.

We conclude that from the perspective of a joint demand system, the pattern of falling end-user net volatility exposure is not puzzling; rather, we argue that it arises from the preferences, risk exposures, and interactions between the demand curves of market makers and end users. Our results are robust across various definitions of net demand and option samples based on moneyness, but the patterns are most pronounced for options that are most sensitive to the VIX index, specifically at-the-money and in-the-money options. Additionally, our conclusions hold when we explicitly control for the impact of the underlying asset (the VIX index) on option prices and quantities within the demand system.

We further contextualize our findings through an analysis of Volmageddon, the most significant volatility event yet, when the VIX index surged over 100% in a single day, rising from 18.44 at the open to 37.32 at the close after nearly a year with low volatility.[3] We confirm that during this high-risk period, market-maker demand shocks strongly dominate end-user demand shocks, leading to a dramatic reversal in market makers' volatility exposures, as they shifted from being net short to net long volatility. We provide additional support for this supply-driven mechanism through a forecast error variance decomposition (FEVD) analysis of another volatility-driven event (the Flash Crash of August 2015), as well as two major crises: the 2007–2009 Financial Crisis and the 2020 COVID-19 crisis. The FEVD results confirm that market makers, who are risk averse and need to manage their inventory, play a dominant role in shaping market outcomes during these periods of elevated volatility risk. End-user volatility demand also increases (shifts right) in high-risk periods, but their equilibrium holdings decline due to the more significant supply reduction by market makers.

Given this finding that market makers play a critical and dominant role in volatility markets during high-risk periods, we provide a more detailed empirical analysis of (the determinants of) their demand curve and inventory management. Our goal is twofold: first, to validate that the estimated market-maker demand curve exhibits properties consistent with the behavior of liquidity providers; and second, to deepen our understanding of the economic forces driving market makers' behavior. We first follow Fournier and Jacobs (2020) and use the CBOE open-close data to construct a daily measure of VIX call option inventory held by market makers, their exposure to volatility (inventory risk), and the daily changes in their wealth. We find that market makers reduce supply when their inventory risk (in absolute terms) increases, but that they increase supply in response to positive wealth shocks. Second, we show that

[3] See Augustin, Cheng, and Van den Bergen (2021) for an analysis of this event.

market-maker demand shifts right when expected VIX futures returns increase, suggesting a speculative determinant of market-maker demand. These patterns are particularly pronounced for short-term options. In contrast, end-user demand does not correlate with expected VIX futures returns across any maturity category. Finally, we find that transaction costs, captured by daily changes in the dollar bid-ask spread, are closely associated with shifts in the market-maker supply curve, with the expected sign. The dollar spread widens during periods of market turmoil when supply contracts, especially for short-maturity options. These stylized facts indicate that market makers respond to elevated volatility risk by adjusting their supply and option spreads in an internally consistent fashion.

In summary, our analysis demonstrates that market makers should not be regarded as passive liquidity providers; instead, they actively manage their inventories and engage in speculative behavior. These actions affect market equilibrium, particularly during high-risk periods. Our findings also validate the use of shocks to market-maker demand, identified through the demand system, as a proxy for option supply and as a useful tool for analyzing how supply influences equilibrium in volatility markets. More broadly, our findings highlight key stylized facts and patterns in the dynamics of end-user net positions and option prices. Finally, our estimates of the demand curves of investors and market makers are useful to understand the implications of policy initiatives that may trigger demand and supply adjustments by end users and market makers in these important financial markets.

The paper proceeds as follows. Section 2 reviews the literature. Section 3 describes the data, presents descriptive statistics, and documents key patterns in the term structure of volatility exposures and option returns. Section 4 introduces and estimates the demand system, and highlights the role of market-maker demand during high-risk periods, the drivers of market-maker demand, and concurrent changes in bid-ask spreads. Section 5 provides robustness checks, including alternative definitions of high-risk periods, net exposure measures, moneyness samples, and VAR specifications. Section 6 discusses potential extensions to the demand system to allow for latent and observable systematic factors, and Section 7 concludes.

2 Literature Review

Our analysis is motivated by the puzzling stylized facts on volatility premia and net demand in high-risk periods first documented by Cheng (2019).[4] We provide a rational explanation for the net demand puzzle. We argue that the decline in investor net demand for volatility is due to contracting supply in high-risk periods and therefore does not constitute a puzzle. Instead, we highlight the critical role of market-maker demand (which can be thought of as supply in a zero-net-supply market) during these periods, as well as their inventory risk management and strategic interactions with end users. Our analysis has two limitations from the perspective of the existing literature. First, while some of the existing literature discusses volatility derivatives more in general (Atmaz and Buffa, 2023), Cheng (2019, 2020) emphasizes patterns in the VIX *futures* market, while we analyze the VIX *option* market. The main reason for this is that the quality of the available data on net demand for VIX options is far superior to that of the VIX futures net demand data; moreover, they are available at a higher (daily) frequency. However, we believe that the mechanism we highlight is also applicable to VIX futures as these two markets are integrated, and quantities and prices are highly correlated. Indeed, we also observe a decline in net demand for VIX futures during high-risk periods, consistent with the patterns in VIX options. The second caveat is that while we address the quantity puzzle highlighted by Cheng (2019), we do not seek to resolve the volatility risk premium puzzle. Analyzing the volatility risk premium requires modeling expected future realized volatility and the associated risk-neutral expectations; our analytical framework is by design restricted to the historical probability measure. Specifically, our framework identifies demand curves based on the intuitive and simple economic assumption of downward-sloping demand curves. Modeling risk premiums requires us to model expectations and investor preferences, which is

[4]See Cheng (2020) and Atmaz and Buffa (2023) for additional discussion of these puzzles.

a much harder problem. We therefore restrict ourselves to the much simpler task of modeling equilibrium VIX prices and quantities.

Our work is also closely related to the literature on demand-based option pricing, which originates with Bollen and Whaley (2004) and Gârleanu, Pedersen, and Poteshman (2009). One of the central themes in this literature is how intermediary inventory risk affects option prices and risk premiums. For important contributions to this literature, see for instance Chen, Joslin, and Ni (2019), Fournier and Jacobs (2020), Ober (2025), Terstegge (2025), Almeida and Freire (2025), and Crescini, Trojani, and Vedolin (2025). The main difference between our work and this existing literature is our explicit focus on quantities, specifically the role of market makers and investors in explaining the puzzling patterns in equilibrium net demand. We explain these patterns by uncovering the latent demand curves, which also requires an empirical setup that is very different from the one used in these studies.

Several recent papers propose equilibrium models to explain the (counterintuitive) switch in sign of the variance risk premium in high-risk periods. Atmaz and Buffa (2023) shows that this pattern arises when low-risk investors dominate a market where risk is transferred among agents with disagreement about volatility expectations. Ghaderi, Kilic, and Seo (2024) offer an explanation based on learning dynamics and investors' preference for variance at the peak of a crisis. Lochstoer and Muir (2022) emphasize the role of slow-moving biased expectations in shaping patterns in the VIX and the variance risk premium. In contrast to these studies, our primary focus is on explaining the (counterintuitive) demand patterns observed in the volatility market. In this sense, our paper is more closely related to Farago, Khapko, and Ornthanalai (2021), who model the joint equilibrium dynamics of put option demand and stock returns in an economy with disappointment-averse investors exhibiting heterogeneous preferences. However, in contrast to these preference-based models, our approach remains agnostic about the underlying investor preferences that drive demand. While this approach does not easily lend itself to integration into parametric structural models, it allows us to quantify the relationship between market participants' demand and equilibrium outcomes without relying on strong assumptions. Our methodology is best described as a bottom-up approach: we start with economically intuitive reduced-form assumptions on demand curves to identify latent demand shifters; then we employ regression analysis to link these estimated shifters to economically motivated variables. This method thereby allows us to infer the underlying preferences and constraints shaping demand.

Our paper is also related to the extensive literature that models VIX options and futures.[5] This literature consistently documents that expected returns on aggregate volatility are negative, especially at short maturities.[6] Our findings confirm that the largest unconditional returns occur at short maturities in the VIX options market. However, our paper differs from this literature because our main focus is on quantities and the time-variation in net demand, rather than option returns and variance risk premiums embedded in VIX and index option markets.[7]

Our empirical investigation uses the pure-sign restriction vector autoregression (VAR) method to identify the latent demand of market makers and end users (Faust, 1998; Canova and De Nicolo, 2002; Uhlig, 2005). This approach is part of the broader framework of structural VAR systems reviewed by Kilian and Lütkepohl (2017). It has been applied to identify demand and supply in various setups, including corporate bonds (Goldberg and Nozawa, 2021), oil markets (Kilian, 2009), intermediary leverage (Fontaine, Garcia, and Gungor, 2023), and index options markets (Jacobs, Mai, and Pederzoli, 2024). Finally, our work is also related to a growing literature on demand-based asset pricing (Koijen and Yogo, 2019; Koijen, Richmond, and Yogo, 2020; Chang, Hong, and Liskovich, 2015; Barbon and Gianinazzi, 2019; Gabaix and Koijen, 2021), but this literature relies on different empirical methods.

[5]See for instance Zhang and Zhu (2006), Mencia and Sentana (2013), Zhu and Lian (2012), Park (2015), Bakshi, Madan, and Panayotov (2015), Wang, Shen, Jiang, and Huang (2017), Lin and Chang (2009), Huang, Schlag, Shaliastovich, and Thimme (2019), Eraker and Yang (2022), and Tong, Huang, and Wang (2022).

[6]See for instance Eraker and Wu (2017), Dew-Becker, Giglio, Le, and Rodriguez (2017), Aït-Sahalia, Karaman, and Mancini (2020), and Johnson (2017).

[7]See, among others, Carr and Wu (2009), Bollerslev, Tauchen, and Zhou (2009), Andersen, Bondarenko, and Gonzalez-Perez (2015), and Andersen, Fusari, and Todorov (2015) for important contributions to this literature.

3 Equilibrium in the Volatility Market: Stylized Facts

We first outline the data sources and present stylized facts regarding the unconditional (average) patterns in volatility demand. We then examine how investors' net volatility positions change in high-risk periods, and we discuss the term structure of returns observed during these periods.

3.1 Patterns in Net Volatility Demand

Our baseline empirical results focus on the VIX call market, for two reasons. First, the VIX call market is considerably larger than the VIX put market. Second, the results for VIX puts are entirely consistent with the results for VIX calls, and therefore reporting results for both VIX calls and puts merely duplicates the results and takes up scarce space. We therefore focus on calls throughout, and Table A.1 in the Appendix reports the main results for puts.

We start by reporting stylized facts on the unconditional distribution of volatility trading in the VIX call option market. The data start in February 2006 and our sample ends in February 2021. Our primary variable of interest is the quantity traded by investors (end users), which is defined as the total number of buys minus the total number of sells by non-market makers. This quantity is often referred to as net demand in the literature. We calculate the time series of this quantity on every day t in the sample from the CBOE Open-Close database by summing the net demand (buy orders minus sell orders) by non-market makers across all traded option series j on day t:[8]

$$ND_t = \sum_j ND_t^j = \sum_j (Buy_t^j - Sell_t^j) \tag{1}$$

Option markets are in zero-net supply, which implies that market makers are the counterparties

[8]Several papers in the existing literature have used the CBOE data to construct net demand for options. For example, Chen, Joslin, and Ni (2019), Dim, Eraker, and Vilkov (2023), and Jacobs, Mai, and Pederzoli (2024) use these data to construct net demand for S&P 500 options, while Ni, Pearson, Poteshman, and White (2021) focus on options on individual stocks. Gu, Guo, Kurov, and Stan (2022) use these data to analyze the net demand for VIX options.

of the above net demand by end users. When net demand is positive, end users are on aggregate net long volatility through their positions in VIX calls, and market makers are on aggregate net short volatility. Net demand is different from volume, which is a non-directional measure of trading intensity. Volume can be computed from the CBOE Open-Close database as the sum of all buys and sell orders by non-market makers across all traded option series j on day t:

$$Volume_t = \sum_j Volume_t^j = \sum_j (Buy_t^j + Sell_t^j) \tag{2}$$

Net demand on day t can be computed for all available options, or by groups identified by option characteristics such as moneyness or maturity. Our baseline results report results by maturity categories. Panels A and B of Table 1 provide summary statistics for VIX call option net demand and volume across five maturity categories, defined by time to expiration: one month or less (category 1), one to two months (category 2), two to three months (category 3), three to four months (category 4), and four to twelve months (category 5). The volume data in Panel B indicate that trading activity is concentrated in the shortest maturities (categories 1 and 2).

[Table 1 about here.]

Panel A shows that, on average, end users are net long VIX calls for all maturities; the largest net long position is for category 2 (one to two months). A positive net demand in VIX call options implies that investors take a net long position in volatility, thus effectively hedging against volatility spikes. The zero-net-supply nature of the options market further implies that the counterparties to end users, i.e., market makers, are on average short volatility, particularly in options with between one and two months to expiration, thereby effectively providing volatility insurance to end users. However, the very high standard deviation of ND_t, particularly for short maturities, suggests considerable day-to-day variation around these average equilibrium positions.

[Figure 1 about here.]

Panel A of Figure 1 complements the summary statistics in Table 1 by plotting the time series of net demand for shorter maturity (with three months or less to maturity) and longer-maturity (with more than three and up to twelve months to maturity) options. While net demand is positive on average, it is indeed highly volatile and frequently switches sign, particularly at the short end of the term structure. Notably, the figure shows a sharp decline in net demand during two major events highlighted in the figure: the COVID-19 crisis (March 2020) and the "Volmageddon" event in February 2018, with short-term options experiencing the steepest decline. This pattern seems puzzling, as it suggests that end-user hedging declines during periods when long volatility exposure may be most valuable.

In summary, these stylized facts document a distinctive pattern in VIX call options trading: end-user net demand is positive on average, but it drops sharply during major volatility events. The next section analyzes more systematically how net demand changes during periods of elevated (volatility) risk.

3.2 Volatility Demand in High-Risk Periods

The literature on the modeling and pricing of volatility and volatility derivatives (e.g., see Eraker and Wu 2017, Eraker and Yang 2022, and Huang, Schlag, Shaliastovich, and Thimme 2019) shows that the volatility risk premium embedded in these instruments compensates investors for the stochastic nature of volatility. The size of the premium therefore depends on the parameters governing the dynamics of volatility, particularly volatility-of-volatility. Moreover, investors use volatility derivatives to hedge against market downturns. The most important stylized fact driving this hedging demand is the robustly negatively correlation between market returns and changes in volatility. Guided by these insights, we define high-risk periods in the VIX option market as those marked marked by extreme realizations of two key measures of volatility risk: (i) changes in the VIX index (ΔVIX), and (ii) the VVIX index, which captures the expected volatility of the VIX.[9]

[Table 2 about here.]

The first two rows of Panel A of Table 2 report differences in net demand and trading volume between high- and low-risk days, defined by the top and bottom quintiles of the ΔVIX (left panel) and VVIX (right panel) distributions for the five maturity categories. The results clearly indicate a sharp decline in net demand for short-term options (categories 1, 2, and 3) on high-risk days, accompanied by a rise in trading volume in categories 1 and 2.

[Figure 2 about here.]

Panel A of Figure 2 provides additional insight into the differences in net demand patterns across risk regimes documented in Table 2. We plot (the term structure of) average VIX call net demand during high-risk (in red) and low-risk (in blue) periods, defined as the top and bottom quintiles of daily VIX changes (ΔVIX), along with the unconditional average (in brown).[10] The red line, representing high-risk periods, shows a pronounced downward shift in the term structure of average net demand: net demand is significantly negative for category 1 and slightly negative for category 3 during high-risk periods. In contrast, net demand on low-risk days is positive across all maturities, like the overall average, highlighting the stark difference in market equilibrium in different volatility risk regimes.

Overall, these results confirm that the patterns in net demand during the financial crisis and Covid-19 periods evident from Figure 1 are more systematically present in the volatility market during times of elevated risk. These findings confirm that the quantity puzzle in the volatility market documented by Cheng (2019) and Atmaz and Buffa (2023) for the VIX futures market is also present in the VIX option market. Before we proceed with a more structural analysis in Section 4, we now argue that these net demand dynamics cannot be explained by exclusively

[9] In Section 5.1, we demonstrate that our findings are robust when using alternative risk indicators.

[10] We present results for a single risk measure for expositional brevity. Figure A.1 presents the corresponding results based on the VVIX, which are similar. Figure A.2 in the Appendix reports the 95% confidence intervals.

considering the actions of investors, which in turn motivates our analysis of the actions of market makers.

[Figure 3 about here.]

As emphasized above, these patterns in net demand are not due to reduced trading activity; in fact, Panel B of Figure 2 clearly shows that trading volume is very high during high-risk periods. A competing explanation for the observed patterns is that investors are closing profitable positions during high-risk periods. Constrained investors may be cashing in their hedges without replacing them, possibly due to liquidity or funding constraints. Panels C and D of Figure 2 partly support this view: net demand computed from closing existing positions by end users becomes increasingly negative during high-risk periods, with an upward-sloping term structure, while net demand computed from opening new positions also declines.[11] However, if this were the entire story, we would expect the overall position of end users in VIX call options to simply decline, or at most drop to zero, during high-risk periods. In fact, these positions turn negative.

We contextualize this by considering the patterns in net demand during two major events in our sample. Figure 3 shows the daily inventory positions for market makers in VIX call options during the Volmageddon (Panel A) and COVID-19 (Panel B) crises.[12] Prior to Volmageddon, market makers held negative inventories, consistent with selling volatility to end users. But just prior to February 5, 2018, inventory spiked sharply, turned positive, and remained elevated for several days, indicating that end users not only closed their long volatility positions but switched to a net short volatility position. A similar pattern emerges during the COVID-19 crisis. While market-maker inventory initially remained negative, it started increasing and turned positive around March 11–12, 2020, coinciding with the WHO's pandemic declaration.

[11] The CBOE Open-Close data distinguishes between trades that open new positions and those that close existing ones. We calculate net open demand as open buy minus open sell orders, and net close demand as close buy minus close sell orders.

[12] We measure daily inventory as the negative of cumulative net demand from firms and customers, aggregated by maturity category.

Inventory stabilized in April but again turned positive in June amid renewed concerns about a second wave. In both episodes, end users did not simply reduce exposure: they actually reversed their positions from net long to net short volatility. These patterns suggest that the sharp drop in net demand is not (fully) attributable to reductions in end-user demand, but instead suggests that more complex equilibrium dynamics involving both demand and supply are driving the market outcome.

3.3 Patterns in Volatility Returns

It is critical to keep in mind that traded quantities in financial markets and the net positions of end users represent equilibrium outcomes. If the supply curve of end users' counterparties (market makers) is not infinitely elastic, equilibrium net demand reflects the intersection of all market participants' demand curves, not just the hedging needs of end users. Prices (or returns) are also determined in equilibrium and adjust in response to shifts in both end-user and market-maker demand. The observed dynamics of market equilibrium are captured by the joint time series of realized prices and traded quantities, which reflect simultaneous shifts in both demand curves.

Therefore, to fully characterize how market equilibrium evolves during high-risk periods, it is essential to examine not only traded quantities (net demand), but also prices. We focus on option returns, calculated as $\frac{P_t - P_{t-1}}{P_{t-1}}$. Panel C of Table 1 indicates that VIX call returns are unconditionally highly negative for short maturities, consistent with the fact that the negative variance risk premium embedded in VIX call options is most pronounced at the short end of the term structure.[13] In contrast, Panel E of Figure 2 shows that returns on high-risk days are positive and that the term structure slopes downward.

From the perspective of a demand system, the observed pattern of low net demand and

[13] See for instance Eraker and Yang (2022) and the return patterns in the VIX futures market (Hu and Liu, 2024) and the SPX variance swap market (Dew-Becker, Giglio, Le, and Rodriguez, 2017). VIX futures returns, reported in Panel D of Table 1, are highly correlated (about 90%) with VIX call returns, confirming the role of VIX calls as effective instruments for gaining exposure to the VIX index.

high returns in VIX call option market during high-risk periods may not be puzzling. As in the demand-supply frameworks of Cohen, Diether, and Malloy (2007) and Chen, Joslin, and Ni (2019), these dynamics can be rationalized by a dominant negative supply shock, or, equivalently, a positive demand shock from market makers who want to reduce their negative exposure to volatility. The underlying mechanism is intuitive: during periods of heightened volatility risk, market makers may become less willing to supply options and/or require higher compensation to do so, resulting in reduced quantities traded at higher prices. The next section formalizes this intuition by estimating a demand system that jointly identifies the demand curves of both market makers and end users.

4 A Market Maker Perspective

This section analyzes the role of market makers in determining market equilibrium in the VIX option market, with the goal of explaining the puzzling drop in net demand during high-risk periods. We start by introducing a demand system that incorporates the demand curves of both end users and market makers. Market-maker demand can also be thought of as supply. Next we discuss the estimation results and the results from a forecast error variance decomposition (FEVD) analysis. Finally, we provide additional evidence in support of the demand-supply framework and highlight the importance of the supply channel by examining the determinants of market-maker demand and the behavior of bid-ask spreads during high-risk periods.

4.1 The Demand System

We model the demand system in the VIX option market using linear reduced-form demand curves, following a bottom-up approach in the spirit of Goldberg and Nozawa (2021) and Jacobs, Mai, and Pederzoli (2024). Rather than deriving demand functions from a utility-maximization framework as in Koijen and Yogo (2019), we start with simple reduced-form relationships between equilibrium price and quantity, and we use the estimation results to infer the underlying preferences and constraints of the various market participants.

The demand system for each option j is given by:

$$\begin{cases} P_{t,j} &= \beta_{MM,j} Q_{MM,t,j} + \varepsilon_{MM,t,j} \\ P_{t,j} &= \beta_{EU,j} Q_{EU,t,j} + \varepsilon_{EU,t,j} \end{cases} \tag{3}$$

where $P_{t,j}$ is the price of option j, and $Q_{MM,t,j}$ ($Q_{EU,t,j}$) is the quantity of option j traded by market makers (end users). The MM and EU subscripts refer to market makers and end users, respectively. $\beta_{MM,j}$ and $\beta_{EU,j}$ represent the (negative) slopes of the demand curves, while $\varepsilon_{MM,t,j}$ and $\varepsilon_{EU,t,j}$ denote the shifters of the curves. Because options are in zero net supply, in equilibrium we have $Q_{MM,t,j} = -Q_{EU,t,j}$, and the market-maker demand curve can equivalently be interpreted as a supply curve. Without loss of generality we define the equilibrium quantity to be the end user quantity, that is, $Q_t = Q_{EU,t,j} = -Q_{MM,t,j}$. Our empirical implementation measures the quantity variable using net demand on day t, and the price variable using returns, which capture price innovations.[14] Note that the quantity variable is therefore also equal to the change in market participants' inventories.

Estimating this type of demand system presents a major challenge: prices and quantities are jointly determined in equilibrium, making it difficult to separately identify the distinct demand shifters for different market participants. However, for our application, which consists of only two types of agents (end users and market makers), the Structural Vector Autoregression (SVAR) methodology with sign restrictions, proposed by Uhlig (2005) and implemented in Goldberg and Nozawa (2021) and Jacobs, Mai, and Pederzoli (2024), provides a straightforward and effective approach to identifying the system. The estimation consists of two main steps:[15] First, we

[14]It is preferable to use price differences rather than levels for statistical reasons. Our use of returns is consistent with the literature on dynamic option pricing models, which usually models the change in the log price, $d\ln(P_t)$.

[15]Here we limit ourselves to an intuitive discussion of the model mechanics. For a detailed discussion of the framework and the estimation procedure, see Appendix A.

estimate a standard Vector Autoregression (VAR) consisting of option returns and net demand (along with their lags) using a Bayesian approach to obtain the reduced-form residuals $u_{MM,t,j}$ and $u_{EU,t,j}$.[16] Second, we orthogonalize the residuals to recover the uncorrelated structural demand shocks $\varepsilon_{MM,t,j}$ and $\varepsilon_{EU,t,j}$, as follows:

$$\begin{bmatrix} u_{MM,t,j} \\ u_{EU,t,j} \end{bmatrix} = A \begin{bmatrix} \varepsilon_{MM,t,j} \\ \varepsilon_{EU,t,j} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{MM,t,j} \\ \varepsilon_{EU,t,j} \end{bmatrix} = \begin{bmatrix} + & + \\ - & + \end{bmatrix} \begin{bmatrix} \varepsilon_{MM,t,j} \\ \varepsilon_{EU,t,j} \end{bmatrix} \tag{4}$$

Identification of these structural shocks relies on sign restrictions imposed on the impact matrix **A**: both end-user and market-maker demand shocks are assumed to raise prices on impact, but, due to the dual nature of the market, they have opposite effects on $Q_{t,j}$, the quantity traded by end users.

Note that the demand system in equation (3), its identification, and the estimation procedure align with basic economic intuition and the standard notion of demand and supply equilibrium in any market. While the toolkit is different, it is also entirely consistent with the structure of the demand system in the equilibrium model of Koijen and Yogo (2019). However, the framework differs from traditional option pricing models, which typically assume that prices respond only to information about future market conditions or discount rates, but not to demand shocks. Traditional models emerge as a special case within our framework: for example, if prices evolve according to the Heston (1993) stochastic volatility model, the slopes $\beta_{MM,j}$ and $\beta_{EU,j}$ are zero, and the two demand equations in equation (3) collapse into a single equation with the price shifter reflecting the expected future dynamics of the underlying asset and its volatility.

We estimate the system separately for five "representative" option series, each corresponding to one of the maturity buckets analyzed in Section 3.1, that is, $j = 1, \ldots, 5$. On each day, the representative option's net demand is defined as the aggregate net demand within the maturity bucket (as introduced in equation (2)), and its return is computed as the average return of

[16] The optimal number of lags is chosen based on the Bayesian Information Criterion (BIC).

the options in that bucket. We deliberately focus on the estimation of option-specific demand curves, which allow us to study differences in demand and supply across maturity buckets. Alternatively one might want to focus on demand curves for the entire VIX option market. Section 6 implements an extension in which the individual option-level shocks are assumed to follow a linear factor structure with loadings on common systematic demand and supply factors. We show that this additional structure does not affect our main conclusions.

4.2 Latent Demands in High-Risk Periods

The main output of the demand-system estimation described in the previous section is a time series of orthogonal demand shocks, or latent demands, $\varepsilon_{MM,t,j}$ and $\varepsilon_{EU,t,j}$, which capture the time-series evolution of the demand curves across the five option maturity categories. Panel C of Figure 1 plots the time series of the thirty-day moving average of the estimated end-user and market-maker demand for short-maturity options (up to three months to expiration) and long-maturity options (between three and twelve months). It is informative to compare these latent demand series with the net demand time series shown in Panel A of Figure 1. Both latent demand series fluctuate substantially over time, alternating between positive and negative values. However, an important difference between the time series of equilibrium net demand and latent end-user demand is that during volatility events such as Volmageddon and COVID-19, net demand drops sharply, while latent end-user demand does not decline; in fact, it slightly increases. Even more importantly, the figure clearly shows a large positive spike in market-maker demand during these periods, indicating a desire for additional long volatility exposure. This qualitative analysis suggests a central role for market makers in determining the decrease in equilibrium net demand observed during high-risk periods.

Panel F of Figure 2 shows that these patterns are more general and not limited to the Volmageddon and COVID-19 episodes. We plot the average term structure of end-user and market-maker demand on high- versus low-risk days. Both demand curves increase when risk is high and decrease when risk is low. The figure also reveals a pronounced downward-sloping term structure during high-risk periods, indicating that the largest increases in demand occur for short-maturity options. Panel A of Table 2 provides statistical confirmation that demand shocks differ significantly between high- and low-risk days, with both demand curves spiking up when risk is high.[17] Panel F of Figure 2 further shows that while the term structures of end-user and market-maker demand appear nearly overlapping during low-risk periods, the market-maker demand curve is consistently higher than the end-user curve on high-risk days. Panel B of Table 2 formally tests and confirms the statistical significance of this difference, and indicates that the strongest effect is observed for maturity category 1.

Overall, the demand system estimation reveals that during periods of market stress, end-user demand shifts right, consistent with increased hedging desire by investors. However, a more pronounced upward shift in market-maker demand curves, which can also be interpreted as a negative supply shock, results in lower equilibrium end user net demand. This mechanism is most evident at the short end of the term structure, which results in a downward-sloping conditional term structure of end-user demand shocks during periods of market turmoil. It is important to note that this analysis does not (seek to) explain why market makers behave this way. It merely shows that market makers appear more constrained on high-risk days, exhibit less willingness to write options, and reduce their short volatility positions. Section 4.4 explores the potential determinants of these shifts in the demand curve through a regression analysis.

4.3 Which Demand Shock Dominates in High-Risk Periods?

In the previous section, we showed that during high-risk periods, the market-maker demand curve shifts right more than that of end users, suggesting that the puzzling decline in equilibrium net demand is driven by a supply-side mechanism. This section formally tests this hypothesis using the forecast error variance decomposition (FEVD) associated with the estimated VAR,

[17] As in Section 3.2, high- and low-risk days are defined using quantiles of the ΔVIX and $VVIX$ variables. Section 5.1 confirms the robustness of the results using alternative measures of risk.

which quantifies and compares the relative contributions of market makers and end users to the variability of future equilibrium net demand.

[Table 3 about here.]

Table 3 reports the difference between the one-step ahead FEVD of net demand attributable to end-user demand versus that attributable to market-maker demand. A positive value indicates that end-user demand explains a greater share of next-day net demand variability, while negative values imply a dominant role for market-maker demand. The results are expressed in percentages, ranging from -100 (entirely driven by market makers) to 100 (entirely driven by end users). Panel A reports the results for the full sample estimation for each of the five different option maturity categories. Overall, market makers and end users contribute almost equally to next-day net demand variability. However, market makers play a slightly larger role at the short end of the term structure: their variance contribution exceeds that of end users by 7% in category 1 and 4% in category 2.

We now test whether market-maker dominance becomes more pronounced during major crisis episodes. Panel B of Table 3 focuses on two major volatility events ("Volmageddon" and the "Flash Crash") which mark the two largest single-day changes in the VIX index in our sample, and Panel C analyzes the peaks of the 2008 financial crisis and the COVID-19 crisis.[18] We re-estimate the demand system using short windows surrounding the events, and we compare the contributions of end user and market-maker demand to next-day net demand.[19]

Panel B of Table 3 shows that during the two major volatility events, market makers play a more prominent role in shaping next-day net demand across all maturities compared to the full-sample results. For instance, in Category 1 (Category 5), their variance contribution exceeds

[18]On February 5, 2018, the rebalancing of leveraged short VIX products triggered a cascade in the VIX market, commonly referred to as "Volmageddon" (see Augustin, Cheng, and Van den Bergen, 2021). On August 24, 2015, the S&P 500 dropped 5% within minutes, an episode widely referred to as the "Flash Crash".

[19]For the two volatility events, we use data windows starting one week before and extending two months after each event date. The resulting data windows are August 8, 2015 to October 24, 2015, and January 29, 2018 to April 5, 2018, respectively. For the financial crisis and COVID-19 crisis, we use data windows from September 22 to November 22, 2008 and from February 16 to April 16, 2020, respectively.

that of end users by approximately 40% (7%) during the Flash Crash and by 16% (8%) during Volmageddon. Panel C of Table 3 further shows that during the financial crisis and the COVID-19 crisis, the influence of market makers also increases relative to the full sample. However, in these cases, the effect is more concentrated at the short end of the term structure, specifically in maturity Category 1 during the financial crisis, and in Categories 1 and 2 during the COVID-19 period.[20]

Overall, our findings confirm that market-maker demand plays a crucial role in the determination of equilibrium net demand, or equivalently, the resulting inventory positions in the VIX call market, particularly during periods when risk is elevated. It is likely that these adjustments reflect responses to inventory constraints, as well as efforts to enhance profitability. The next section investigates these potential determinants of market-maker demand more closely using a regression analysis.

4.4 The Determinants of Market-Maker Demand

This section examines the economic determinants associated with shifts in the market-maker demand curve. Our goal is to empirically identify factors that correlate with, and help distinguish, market maker behavior from that of end users. Specifically, we test two hypotheses: (i) whether observed demand curve shifts are consistent with inventory management considerations; and (ii) whether they align with expectations about future VIX levels and changes.

The first channel investigates if market makers shift their demand curve to manage inventory constraints. Our prior is that when facing inventory pressure, market makers will provide less liquidity to end users. This behavior is consistent with earlier evidence that market-maker demand drives future equilibrium net demand. Following Fournier and Jacobs (2020), we construct two daily measures of market maker constraints. The first is a measure of daily

[20]Unlike the results in Panel B, we also observe positive FEVD values for some maturities during these crises, indicating that investor hedging demand remained strong in the VIX call option market even during periods of heightened risk.

changes in their volatility exposure, denoted ΔInventory Risk as in Fournier and Jacobs (2020), computed as the daily change in market makers' delta-weighted inventory across all option series. The second is a measure of daily changes in their wealth, denoted ΔWealth, which accounts for delta-hedged profits and losses from their inventory positions, as well as revenues from the bid-ask spread.[21]

[Table 4 about here.]

Table 4 reports the results of regressing market-maker and end-user demand shocks on $\Delta\text{Inv Risk}_{t-1}$ and $\Delta\text{Wealth}_{t-1}$.[22] The second row of Table 4 shows that market-maker demand is significantly related to past inventory risk in one-month options (category 2), where market makers face the largest positive order imbalance from end users (as documented in Table 1). The negative coefficient indicates that, when holding a larger negative volatility position, market makers strategically shift their demand curve rightward, or equivalently, reduce supply, to mitigate exposure. In contrast, end-user demand does not respond to past changes in market-maker inventory risk. The third row of Table 4 shows that, following a positive wealth shock, market makers tend to increase supply (decrease demand) across maturities, as reflected in lower demand shocks. Conversely, end-user demand rises with past changes in market-maker wealth, suggesting an overall expansion in market activity after positive shocks to market maker wealth. Taken together, these results confirm that supply contracts when inventory constraints

[21] Specifically, daily changes in market maker wealth are calculated as the sum of delta-hedged profits and losses (P&L) and bid-ask spread revenue, net of exchange fees, aggregated across all option series. The delta-hedged P&L for option series j is calculated as:

$$\text{P\&L}_j = \text{Inventory}_{j,t-1} \times \left(P_{j,t} - P_{j,t-1} - \Delta_{j,t-1} \times (F_t - F_{t-1})\right),$$

where $P_{j,t}$ is the option price, and F_t is the underlying futures price. We also account for bid-ask spread revenue, net of exchange fees, based on liquidity provision on both sides of the order book:

$$BA_j = \min(Buy_j, Sell_j) \times (\text{Dollar Spread}_j - \text{Fee}),$$

The fee is $0.05 when the option price is below $0.11, and $0.23 when it exceeds that threshold (for reference, see the CBOE fee structure: *https://www.cboe.com/us/options/membership/fee_schedule/cone/*).

[22] We use the first lag of these variables because market maker inventory and profits on day t are mechanically linked to the equilibrium quantity traded on the same day.

are binding. These findings suggest that our estimates of market maker supply have significant economic content. They also suggest that the supply contraction observed in high-risk periods, which helps explain the puzzling drop in end-user net demand, may at least partly reflect concerns about inventory.

Next we explore the hypothesis that market makers may behave more strategically than end users, who are primarily motivated by hedging needs and presumably less sensitive to expectations of future profits. Specifically, we test whether market makers adjust their demand curves in response to expected future VIX returns in an effort to enhance inventory profitability. We proxy these expectations using the expected return on a long VIX futures position, following the approach in Cheng (2019).[23]

The regression results in the first row of Table 4 show that market-maker demand shocks are significantly and positively related to expected VIX returns, with decreasing loadings and R-squares as a function of maturity. When expected returns on volatility increase, market makers shift their demand curves to the right, increasing inventory and potentially profiting from greater exposure to the expected positive volatility payoffs. This effect is particularly pronounced for short-term options in maturity categories 1 and 2. Further supporting the interpretation that market makers behave strategically and maximize profits, Panel A of Table A.2 in the Appendix compares average VIX option returns on days when market makers are net long volatility through VIX call options versus days when they are net short.[24] The results show that option returns are positive when market makers are long, and significantly negative when they are short. The difference is statistically significant, suggesting that market makers are, on average, increasing profits when adjusting inventory.

[23]We obtained the daily expected VIX futures returns, computed as $\left[\frac{E_t[VIX_T]}{F_t}\right]^{\frac{21}{T-t}} - 1$, from the author's website, where F_t is the current price of the VIX future expiring next month, and $E_t[VIX_T]$ is the ARMA forecast of the VIX at maturity. See Cheng (2019) for details.

[24]For this analysis, we compute market makers' volatility positions by delta-weighting their inventories across all VIX call options in the five maturity categories, and we calculate average option returns by taking the average of individual option returns.

In contrast, the regression results in Table 4 show that end-user demand shows no sensitivity to expected VIX futures returns. This does not imply that end users are irrational. One explanation is that end users are primarily or exclusively motivated by hedging concerns. An alternative explanation, consistent with the model in Lochstoer and Muir (2022), is that investors form subjective expectations about volatility and potentially display an excessive mean reversion bias, which leads to lower correlations between their demand and objective expectations. Moreover, end users may respond more slowly to rising economic risk. This slow adjustment is also consistent with the model in Lochstoer and Muir (2022), which explicitly allows for sluggish investor reactions to changes in volatility conditions. This interpretation also aligns with our earlier evidence presented in Table 2, which shows that while end-user demand increases in response to heightened volatility risk, it increases less than market-maker demand. The interaction between a sharply adjusting market-maker curve and a less responsive end-user curve may also help explain the observed decline in the variance risk premium during high-risk periods.[25] Intuitively, our demand curve estimates suggest that when risk increases, VIX option prices increase due to upward shifts in both curves. However, because investors revise their expectations and demand more slowly than market makers, the increase in option prices does not fully reflect the rise in expected future volatility, which results in a negative variance risk premium.

In summary, this section shows that market makers increase their demand for options when expected profits from holding long VIX positions are high, reduce their supply when their inventory risk increases (in absolute value), and expand their supply following a positive shock to their wealth. These findings suggest that market makers do not merely provide liquidity, but strategically manage inventory risk and profits.

[25]Panel B of Table A.2 in the Appendix confirms the decline in the VIX premium on high-risk days documented by Cheng (2019), based on our definition of high-risk days.

4.5 Bid-Ask Spreads in High-Risk Periods

Our findings indicate that market makers behave strategically by scaling back supply during high-risk periods and actively managing inventory risk to enhance profitability. However, market makers are not only compensated by returns on their inventory, but also via the bid-ask spread. When constrained, they are therefore likely to adjust both inventory positions and spreads in a consistent manner. We therefore complement our analysis of VIX option market equilibrium by examining bid-ask spreads during turbulent periods. We expect (i) bid-ask spread changes to be closely related to supply shocks, and (ii) patterns in the term structure of bid-ask spreads on high-risk days to reflect market makers' constraints.

We define the spread as the dollar difference between the end-of-day best ask and bid prices reported by OptionMetrics for each option series. Daily spreads are computed within each maturity category by averaging across all option series in the sample. We focus on the dollar spread, because it reflects the actual trading costs and represents the earnings of liquidity providers who buy at the bid and sell at the ask while maintaining a neutral position.[26]

[Table 5 about here.]

Panel A of Table 5 presents summary statistics on the term structure of daily bid-ask spreads for VIX call options. Spreads are notoriously wide in the options market, and VIX options are no exception. A market maker buying at the bid and selling at the ask earns about 35 cents per option in category 1, and 20 to 30 cents for the longer maturities.[27] The spread's standard deviation is also high, particularly at the short end of the term structure, indicating significant time-series variation.

[26]An alternative measure is the relative spread, defined as the dollar spread divided by the mid-option price. While this better captures transaction costs from the investor's perspective, the dollar spread is a better proxy for the earnings of liquidity providers.

[27]Investors often pay less than the quoted spread due to price improvement protocols that favor uniformed order flows such as retail trades. However, quoted and realized spreads are usually positively correlated, with the quoted spread serving as an upper bound on execution costs for riskier trades.

Panel B of Table 5 shows the differences between the average spread on high- and low-risk days, based on the risk indicators discussed in Section 3.2 (the change in the VIX index and the level of the VVIX). On high VVIX days, spreads rise significantly. The term structure is downward sloping, indicating that market makers widen the spreads more for short-maturity options on high-risk days. These changes are economically significant: for maturity category 1, the difference in spreads between high and low VVIX days is 75 cents, which is about two times the unconditional average of 35 cents.

This connection between the dollar spread and turmoil in volatility markets suggests that market makers actively manage spreads, especially when they face tighter constraints. To further validate this hypothesis, Panel C of Table 5 presents regressions of daily changes in the dollar spread on the demand shocks of market makers and end users. The results show that when market makers shift their demand curve to the right, signaling their efforts to reduce negative inventory, the dollar spread increases. Similarly, when end-user demand increases, the spread also increases, suggesting that market makers seek compensation for providing liquidity. However, the effect of end-user shocks is less strong, with lower loadings and R-squares, especially for maturity categories 1 and 2. The difference is most pronounced in category 2, where the coefficient on market-maker shocks is twice as large as that for end-user shocks, and the R^2 is significantly higher. This confirms that the dollar spread is more closely linked to shifts in market-maker demand.

In summary, this section documents that variations in the dollar spread are closely related to shifts in market-maker demand with the expected sign, suggesting that market makers manage their positions by adjusting mid-prices, traded quantities, and transaction costs in an internally consistent fashion.

5 Robustness

This section presents robustness checks and additional analyses. First, we re-examine the average levels and term structures of equilibrium net demand, returns, latent demands, and spreads across high- and low-risk periods based on alternative measures of risk. Next, we repeat our baseline empirical analysis using option samples segmented by moneyness categories, using samples of out-of-the-money (OTM), at-the-money (ATM), and in-the-money (ITM) options. We also assess the sensitivity of our baseline results to alternative definitions of net demand.

5.1 Alternative Measures of Risk

In our baseline analysis, we examine differences in equilibrium net demand and latent demand between high- and low-risk periods, using two proxies for risk: daily changes in the VIX, and the VVIX level. To investigate the robustness of our findings, we now re-examine the differences in (the term structure of) equilibrium net demand, returns, latent demands, and spreads using alternative risk measures: the daily change in unstandardized risk-neutral skewness ($\Delta Skew$), computed according to Bakshi and Kapadia (2003),[28] daily returns on the S&P 500 index ($r_{\text{S\&P500}}$), and the level of the VIX index.

[Table 6 about here.]

Panel A of Table 6 compares average option returns and net demand on high- and low-risk days using these alternative risk proxies.[29] Consistent with our baseline results, returns on short-maturity options (category 1) are higher on high-risk days and equilibrium net demand is lower. We find higher returns across maturities and risk measures, but the decline in net demand is more sensitive to the risk proxy. When using the bottom quintile of $\Delta Skew$ or $r_{\text{S\&P500}}$ to define high-risk periods, we observe a reduction in net demand for short maturities. In contrast,

[28] We use non-standardized skewness to distinguish asymmetry risk from volatility risk.

[29] Since ΔSk and $r_{\text{S\&P500}}$ are more negative during high-risk periods, for these two risk proxies we define high-risk days as those in the bottom quintile and low-risk days as those in the top quintile.

when using the top quintile of the VIX level to define high-risk periods, we observe a decline in net demand for all maturities. The largest decline occurs for maturity category 2, which has the highest unconditional equilibrium net demand (see Panel B of Table 1). Panel A also decomposes net demand into its net open and net close components. When risk is proxied by $\Delta Skew$ or $r_{\text{S\&P500}}$, investors tend to unwind existing long positions more aggressively, while opening a limited number of new net long positions. In contrast, when high-risk periods are proxied using the VIX level, we observe a distinct pattern: investors reduce the number of new net long positions in short-term options, while they close existing long positions in long-term options more aggressively.

Both market maker and end-user demand increase on high-risk days, regardless of the risk proxy. Panel B also shows that while both demands are on average positive during high-risk periods, the increases in market-maker demand is larger. The relative magnitudes of these demand increases depend on the risk measure: when using $\Delta Skew$ or $r_{\text{S\&P500}}$, the effects are larger for short-maturity options (category 1), whereas when using the VIX index, the effects are larger for longer maturities (category 5). These patterns suggest that different risk measures highlight different inventory risks faced by market makers.

Finally, the last row in Panel A shows that dollar spreads widen significantly on high-risk days, particularly for short-maturity options, except when high-risk periods are defined using the bottom quintile of $\Delta Skew$. This finding further supports the view that market makers also adjust transaction costs in response to higher risk.

5.2 Results by Option Moneyness

The sample of VIX call options used in the main analysis includes options across all moneyness categories. We now separately analyze options that are out-of-the-money (OTM), with $0.125 < \Delta \leq 0.375$; at-the-money (ATM), with $0.375 < \Delta \leq 0.625$; and in-the-money (ITM), with $0.625 < \Delta \leq 0.875$. Moneyness on day t is determined by the option's delta on day $t-1$, as reported by OptionMetrics.

[Table 7 about here.]

Panel A of Table 7 presents the unconditional term structure of net demand by moneyness category. Net demand is generally positive across categories, indicating that investors typically hold net long positions in VIX call options regardless of moneyness. Panel B reports the difference in net demand between high- and low-risk days. Overall, net demand is lower on high-risk days for ATM and ITM options, especially for short maturities, consistent with the findings from the baseline sample which includes all options. The evidence is less strong for the OTM sample. While most coefficients are negative, they are statistically insignificant. The only (marginally) significant coefficient for the difference between high- and low-risk days in OTM options is a positive net demand difference in maturity category 5, when using the VVIX as the risk proxy.

Panel C examines the conditional term structure of demand shocks, similar to the baseline analysis in Table 2. This evidence is based on VARs estimated using each of the three moneyness samples separately. Once again, the results for ATM and ITM options largely mirror those of the baseline analysis: shocks are positive and high on high-risk days for both market makers (MM) and end users (EU), but larger for market makers, especially at the short end of the term structure. The estimated effect is stronger for ITM options compared to ATM options. For OTM options, there is less evidence of significant differences in MM and EU shocks on high-risk days.

Overall, these results suggest that the results in Section 3.2 and 4 are mainly driven by ITM and ATM options. This finding is intuitively plausible and highlights the role of options' sensitivity to VIX as a key risk factor for market makers. During turbulent periods, market makers are particularly interested in reducing inventory in options that carry higher exposure to volatility.

5.3 The Definition of Net Demand

Our baseline analysis uses net demand in equation (2), which measures the net number of contracts (buys minus sells) purchased by end users or, equivalently, the net number of contracts supplied by market makers. This measure is the most obvious input for our analysis, because it proxies the total daily change in market makers' inventory.

However, the literature has used alternative plausible measures of net demand. This section considers some of these alternative demand measures. A first alternative, which we denote as $ND2_t$, weighs the net demand of each option series by its absolute delta, accounting for the different risk exposures of options with different moneyness to the underlying VIX index. It has been used in, among others, Holowczak, Hu, and Wu (2014) and Jacobs and Mai (2024).

$$ND2_t = \sum_j (Buy_t^j - Sell_t^j)|\Delta_j| \tag{5}$$

Like the baseline net demand measure, $ND2_t$ tracks changes in market makers' inventory. However, instead of measuring inventory in contracts, it expresses it in terms of shares of the underlying asset (in this case, the VIX). Based on our analysis of different moneyness categories in Section 5.2, we expect this measure to yield qualitatively similar, if not stronger, results compared to our baseline analysis.

[Table 8 about here.]

Table 8 presents the results, which are indeed largely consistent with those in Table 1 and 2 that use the baseline net demand variable. Panel A indicates that unconditionally, $ND2$ is positive for all maturity categories, with a very small negative value in category 1 as the only exception. Panel B documents that on high-risk days, the term structure of $ND2$ shifts downward, confirming that end users reduce their net long positions in high-risk periods. Panel C shows that demand shocks for both MM and EU are positive and large on high-risk days, with

MM demand shocks consistently exceeding EU demand shocks, especially at the short end of the term structure. Once again this aligns with our findings obtained using ND.

The second alternative net demand measure we consider, which we denote by $ND3_t$, scales the net number of contracts purchased by investors by the total volume traded on day t:

$$ND3_t = \frac{\sum_j (Buy_t^j - Sell_t^j)}{\sum_j (Buy_t^j + Sell_t^j)} \tag{6}$$

This measure, used for example in Muravyev (2016), is a scaled version of our baseline net demand measure and is bounded between -1 and 1. A value of 1 indicates that all orders are buys, while a value of -1 means all orders are sells. ND and $ND3$ capture different aspects of the order flow. While ND tracks changes in market-maker inventory, $ND3$ captures the directional uniformity of the total order flow. Intuitively, the same change in market-maker inventory can produce very different $ND3$ values when scaled by volume, and similar $ND3$ values can result from very different levels of order flow when expressed in contracts.

Panel A of Table 8 shows that $ND3$ is positive across all maturity categories, with a monotonically increasing term structure, indicating that order flow as a percentage of total volume becomes more directional in longer-term options. Panel B documents that on high-risk days, the term structure of $ND3$ shifts downward, while Panel C shows that both EU and MM demand shocks are positive and high during high-risk days, with MM shocks generally exceeding those of EU. These findings are consistent with earlier results using ND, albeit less statistically significant.

However, the results for ND and $ND3$ differ in the term structure dimension. While the ND demand measure leads to more pronounced effects at the short end of the term structure, the results based on $ND3$ do not yield a clear maturity pattern. In fact, Panel B shows that on high-risk days, $ND3$ experiences a larger decline at longer maturities, likely because $ND3$ is unconditionally higher for longer-term options. Additionally, Panel C indicates no clear term structure in the strength of the two demand shocks, which may be due to high volumes at the short end that are heavily influenced by end user activity.

Overall, these results based on alternative net demand measures confirm the shift in order flow from end users to market makers during periods of market turmoil. The VAR estimates also confirm the greater importance of market-maker demand shocks during high-risk periods. The critical difference is that the proxies that more closely track the changes in the dollar value of market-maker inventory, such as ND and $ND2$, produce more significant results and additionally reveal significant term structure patterns, highlighting that market makers are highly focused on managing the risk of short term options in their portfolios during periods of market distress.

6 Extensions

We introduce several potential extensions to our framework to allow for latent and observable factors. We use these extensions to discuss how our setup is related to the existing option valuation literature, as well as the main dimensions in which it is different. We also implement and estimate several of these extensions, and discuss their implications.

6.1 Incorporating Latent and Observable Factors

Following Black and Scholes (1973) and Heston (1993), most of the existing option valuation literature starts from the dynamics of the underlying security. Our approach is different in several dimensions; we consider two of them absolutely critical. First, existing approaches exclusively model price (dynamics), while we study quantity as well as price. Second, existing option pricing models typically start from a factor model. In the Black-Scholes case, the underlying security return is the sole factor. In the case of the Heston (1993) model and its many generalizations, the variance of the underlying security is added as a second factor, or multiple factors are used that are aggregated up to the variance of the underlying. An interesting distinction between these popular factors is that while the return of the underlying security is observable, the variance of the underlying and/or its components are most generally thought of as latent or unobservable.

We now show that our framework is actually closely related to these alternative models, in the sense that it can be easily extended to include latent and/or observable factors. However, a critical distinction in the context of our framework is to decide whether we want to model these factors as endogenous or exogenous. Note that in most existing models this distinction is not addressed, because they are exclusively focused on the dynamics of the equilibrium price. To illustrate the relation between our approach and the existing literature, consider the following straightforward extension of equation (A.5) in the Appendix for options with maturity j:

$$\begin{bmatrix} P_{t,j} \\ Q_{t,j} \end{bmatrix} = \begin{bmatrix} \alpha_j^{MM} \\ \alpha_j^{EU} \end{bmatrix} + \sum_{i=1}^{l} \begin{bmatrix} b_{MM,i,j}^{P} & b_{MM,i,j}^{Q} \\ b_{EU,i,j}^{P} & b_{EU,i,j}^{Q} \end{bmatrix} \begin{bmatrix} P_{t-i,j} \\ Q_{t-i,j} \end{bmatrix} + \begin{bmatrix} k_{1,j} \\ k_{2,j} \end{bmatrix} \mathbf{F_t} + A_j \begin{bmatrix} \boldsymbol{\varepsilon}_{j,t}^{MM} \\ \boldsymbol{\varepsilon}_{j,t}^{EU} \end{bmatrix}$$

where F_t is a factor.[30] We think of this factor as systematic because it affects all option samples j. In the option pricing literature such systematic factors can be observable, such as the return on the underlying security, or latent, like the variance of the underlying security. However, both latent and observable factors are generally thought of as exogenous. In our setup, it is possible to instead include the factor F_t among the endogenous variables of the system. On the other hand, an exogenous factor FEX_t can be thought of as a special case of a three-variable VAR which imposes restrictions in the matrix of lag coefficients (b matrix) and in the contemporaneous impact matrix A_j, as follows:

[30] For expositional simplicity we consider the case of a single factor, but it is straightforward to generalize this to the case of multiple factors.

$$\begin{bmatrix} P_{t,j} \\ Q_{t,j} \\ \mathbf{FEX_t} \end{bmatrix} = \begin{bmatrix} \alpha_j^{MM} \\ \alpha_j^{EU} \\ \alpha^{FEX} \end{bmatrix} + \sum_{i=1}^{l} \begin{bmatrix} b^P_{MM,i,j} & b^Q_{MM,i,j} & b^{FEX}_{MM,i,j} \\ b^P_{EU,i,j} & b^Q_{EU,i,j} & b^{FEX}_{EU,i,j} \\ 0 & 0 & b^{FEX}_{FEX,i} \end{bmatrix} \begin{bmatrix} P_{t-i,j} \\ Q_{t-i,j} \\ \mathbf{FEX_{t-i}} \end{bmatrix} + \begin{bmatrix} + & + & * \\ - & + & * \\ 0 & 0 & * \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon}^{MM}_{j,t} \\ \boldsymbol{\varepsilon}^{EU}_{j,t} \\ \boldsymbol{\varepsilon}^{FEX}_{t} \end{bmatrix} \tag{7}$$

where $*$ indicates an unrestricted matrix entry. In words, an exogenous factor does not respond to the lagged or contemporaneous values of the other variables, but it can contemporaneously affect them.[31] The resulting restricted structural VAR can be estimated following Lütkepohl (2005) and Kilian and Lütkepohl (2017).[32]

6.2 Modeling the Underlying VIX

When considering factors F_t, the first candidate that comes to mind is the underlying security. We therefore implement an extension of the model that explicitly incorporates the effect of the VIX index on option prices. Specifically, we estimate an extended VAR that includes ΔVIX as an additional variable alongside price and quantity. We implement the general case where the VIX is treated as endogenous, but as discussed above it is possible to implement a restricted version where the VIX is exogenous. The extended VAR model features three equations and, consequently, three shocks: the two demand shocks (market-maker and end-user), as in the baseline analysis, and a new risk shock, as follows:

[31]We can further relax the restrictions in equation (7), because a factor is still exogenous if it is affected by lagged values of the other variables, provided it is not affected by their contemporaneous values.

[32]Identification is thus once again achieved using the sign restrictions. Alternatively, the projection of the observables on the factors can be used to generate additional identifying restrictions.

$$
\begin{bmatrix} P_{t,j} \\ Q_{t,j} \\ \mathbf{\Delta VIX_t} \end{bmatrix} = \begin{bmatrix} \alpha_j^{MM} \\ \alpha_j^{EU} \\ \alpha_j^{\Delta VIX} \end{bmatrix} + \sum_{i=1}^{l} \begin{bmatrix} b_{MM,i,j}^{P} & b_{MM,i,j}^{Q} & b_{MM,i,j}^{F} \\ b_{EU,i,j}^{P} & b_{EU,i,j}^{Q} & b_{EU,i,j}^{F} \\ b_{\Delta VIX,i,j}^{P} & b_{\Delta VIX,i,j}^{Q} & b_{\Delta VIX,i,j}^{F} \end{bmatrix} \begin{bmatrix} P_{t-i,j} \\ Q_{t-i,j} \\ \mathbf{\Delta VIX_{t-i}} \end{bmatrix} + \begin{bmatrix} + & + & * \\ - & + & * \\ * & * & * \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon}_{j,t}^{MM} \\ \boldsymbol{\varepsilon}_{j,t}^{EU} \\ \boldsymbol{\varepsilon}_{t}^{\Delta VIX} \end{bmatrix} \tag{8}
$$

where $*$ once again indicates an unrestricted matrix entry. To estimate this extended VAR and orthogonalize the shocks, we restrict the impact of demand shocks on price and quantity using the same restrictions applied in Section 4, while allowing the effect of demand shocks on ΔVIX and the impact of the new risk shock on the variables to remain unrestricted.[33]

[Table 9 about here.]

For robustness we also analyze the impact of the underlying VIX through an analysis that estimates the demand system from Section 4 using delta-hedged returns as price variable instead of simple option returns. Table 9 reports the average estimated shocks for market makers and end users using delta-hedged returns (Panel A) and the extended VAR (Panel B) during high-risk days, defined by the top 20% of VVIX days or the bottom 20% of S&P 500 days.[34] The results consistently indicate that, during high-risk periods, both market-maker and end-user shocks are positive and high, signaling a rightward shift in both demand curves. However, in line with our previous findings, the increase in market-maker shocks exceeds that of end-user shocks, particularly at the short end of the term structure. This suggests a reduction in market-maker supply on high-risk days, significantly influencing market equilibrium.

We conclude that our main conclusions on volatility demand are not changed by explicitly taking into account the impact of the dynamics of the underlying VIX index on equilibrium price and quantity.

[33]The estimation follows the same procedure as before, with an additional step that discards impact matrices with two columns that display identical sign pattern. This step is required for identification, as outlined in Kilian and Lütkepohl (2017).

[34]In this analysis, we do not consider the risk variable ΔVIX as a criterion for defining high-risk days to avoid potential mechanical effects arising from its inclusion in the VAR. Instead, we use S&P 500 returns.

6.3 Modeling Other Observable Factors

Again by analogy with the existing literature on dynamic option pricing, another candidate factor F_t is the (stochastic) variance of the underlying VIX, which would be typically modeled as latent. The presence of a latent VIX variance substantially complicates estimation and identification, and we therefore keep it for future research. Note that this complication is not specific to our modeling approach. Estimation of dynamic option pricing models with latent variables is inherently difficult and computationally intensive.

A more straightforward avenue to analyze the importance of the VIX variance is to use the observable VVIX and include it in the VAR as in equation (8). We conduct this analysis with both the level and the first difference of VVIX. Table A.3 reports the results. Once again our main conclusions on volatility demand are not affected.

Finally, while we believe the VIX is the most logical factor to include in the VAR, some may be interested in proxies for the (physical) variance of the S&P 500 stock market index that underlies the VIX. Table A.3 therefore also reports results of an analysis that includes the change in the realized index variance, ΔRV.[35] Our conclusions are also robust to the inclusion of ΔRV in the VAR.

6.4 Identifying Latent Common Factors

A potential critique of specifying observable and latent factors is that there may be other latent factors affecting option prices, and omitting them may bias estimation results. It may therefore be preferable to not take a stance on the factors and let the data identify them. There are various avenues available to implement latent common factors. A straightforward one is to focus on the shocks themselves. Specifically, we extend our framework by assuming that the option-specific shocks are driven by common systematic components. Empirically, this extension is

[35]The Oxford-Man Institute of Quantitative Finance provides daily realized variance data based on 5-minute intraday returns. We compute annualized realized volatility by taking the square root of this variance and multiplying it by $\sqrt{252}$. Daily changes in realized variance (ΔRV) are then used in VAR estimation.

supported by a principal component analysis of the time series of shocks across the five maturity categories: the first three components explain approximately 80% of the total variance. The first component alone accounts for 57% of the variation in market-maker shocks, and 51% of the variation in end-user shocks.

To allow for latent common factors, note that asset pricing theory commonly imposes a linear factor structure on returns, which are the key variable of interest. In our setting, however, both returns and quantities are jointly determined and informative about the equilibrium. If we impose a standard linear factor structure on returns and extend this assumption to include quantities, it follows from the linearity of the demand curves that the resulting supply and demand shocks will also exhibit a common linear factor structure. Formally, assuming that a single systematic factor drives the maturity-specific shocks, the demand system for options with maturity j can be expressed as:

$$\begin{bmatrix} P_{t,j} \\ Q_{t,j} \end{bmatrix} = \begin{bmatrix} \alpha_j^{MM} \\ \alpha_j^{EU} \end{bmatrix} + \sum_{i=1}^{l} \begin{bmatrix} b^P_{MM,i,j} & b^Q_{MM,i,j} \\ b^P_{EU,i,j} & b^Q_{EU,i,j} \end{bmatrix} \begin{bmatrix} P_{t-i,j} \\ Q_{t-i,j} \end{bmatrix} + A_j \begin{bmatrix} \beta_{1,j}\boldsymbol{\varepsilon}_t^{MM} \\ \beta_{2,j}\boldsymbol{\varepsilon}_t^{EU} \end{bmatrix}$$

where $\boldsymbol{\varepsilon}_t^{MM}$ and $\boldsymbol{\varepsilon}_t^{EU}$ denote the common systematic supply and demand shocks, respectively. While such systematic factors can be proxied in various ways, a natural choice is to use the demand and supply shocks estimated from the full sample of VIX call options (including all moneyness and maturities). We follow this approach and subsequently estimate the factor loadings $\beta_{1,j}$ and $\beta_{2,j}$ by regressing the option-specific shocks on these systematic factors. Table 10 confirms that option-specific shocks load strongly on the systematic demand and supply factors, which explain a substantial portion of their variation, ranging from 23% to 65%, depending on maturity. Most importantly, our conclusions regarding market maker behavior and the determination of equilibrium net demand are confirmed when we use these projections instead of the maturity-specific demand and supply.

[Table 10 about here.]

In summary, modeling maturity-specific volatility demands as linear functions of a common systematic factor is supported by the data, and this extension does not affect the paper's main conclusions.

7 Conclusion

VIX futures and option markets have grown rapidly since their introduction, mainly because these securities can be used to hedge against market downturns. Consistent with this intuition, end users are on average net long VIX call options to hedge their long position in the market index. However, they paradoxically reduce these net long positions in high-risk periods. We resolve this puzzle by recognizing that the net long or short position of end users at any point in time is an equilibrium outcome that results not only from their demand curve, but also from the demand curve of market makers. Because these option markets are in zero net supply, the market-maker demand curve can equivalently be thought of as a supply curve.

We use a structural VAR with sign restrictions to estimate the time series of end users' and market makers' latent demand curves from the equilibrium net positions of end users and returns. Our findings indicate that both end user and market-maker demand curves shift right during periods of market turmoil, but the change in market-maker demand dominates, especially for options with short maturities. The equilibrium outcome in these high-risk periods is therefore characterized by reduced net long positions of end users and high returns on long volatility positions.

Given this finding that market-maker demand is the main determinant of equilibrium in this market, we analyze the determinants of market-maker demand. Market makers tend to reduce supply (increase demand) when inventory risk rises, yet expand supply in response to positive wealth shocks. Market-maker demand is also related to expected profits on the volatility positions, while this is not the case for end-user demand. Additionally, we find that bid-ask spreads widen during turbulent times, suggesting that market makers also adjust spreads to manage inventory. Once again these patterns are particularly strong for short-maturity options.

Overall, our findings highlight the strategic actions of market makers, who aptly manage inventory risk and maximize profits while providing liquidity.

References

Aït-Sahalia, Yacine, Mustafa Karaman, and Loriano Mancini, 2020, The term structure of equity and variance risk premia, *Journal of Econometrics* 219, 204–230.

Almeida, Caio, and Gustavo Freire, 2025, Demand in the option market and the pricing kernel, *Working Paper*.

Andersen, Torben G, Oleg Bondarenko, and Maria T Gonzalez-Perez, 2015, Exploring return dynamics via corridor implied volatility, *Review of Financial Studies* 28, 2902–2945.

Andersen, T. G., N. Fusari, and V. Todorov, 2015, The risk premia embedded in index options, *Journal of Financial Economics* 117, 558–584.

Atmaz, Adem, and Andrea M Buffa, 2023, Volatility disagreement and asset prices, *Working Paper*.

Augustin, Patrick, Ing-Haw Cheng, and Ludovic Van den Bergen, 2021, Volmageddon and the failure of short volatility products, *Financial Analysts Journal* 77, 35–51.

Bakshi, Gurdip, and Nikunj Kapadia, 2003, Delta-hedged gains and the negative market volatility premium, *Review of Financial Studies* 16, 527–566.

Bakshi, Gurdip, Dilip Madan, and George Panayotov, 2015, Heterogeneity in beliefs and volatility tail behavior, *Journal of Financial and Quantitative Analysis* 50, 1389–1414.

Barbon, Andrea, and Virginia Gianinazzi, 2019, Quantitative easing and equity prices: Evidence from the ETF program of the Bank of Japan, *Review of Asset Pricing Studies* 9, 210–255.

Black, Fischer, and Myron Scholes, 1973, The pricing of options and corporate liabilities, *Journal of Political Economy* 81, 637–654.

Bollen, Nicolas PB, and Robert E Whaley, 2004, Does net buying pressure affect the shape of implied volatility functions?, *Journal of Finance* 59, 711–753.

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected stock returns and variance risk premia, *Review of Financial Studies* 22, 4463–4492.

Canova, Fabio, and Gianni De Nicolo, 2002, Monetary disturbances matter for business fluctuations in the G-7, *Journal of Monetary Economics* 49, 1131–1159.

Carr, Peter, and Liuren Wu, 2009, Variance risk premiums, *Review of Financial Studies* 22, 1311–1341.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2015, Regression discontinuity and the price effects of stock market indexing, *Review of Financial Studies* 28, 212–246.

Chen, Hui, Scott Joslin, and Sophie Xiaoyan Ni, 2019, Demand for crash insurance, intermediary constraints, and risk premia in financial markets, *Review of Financial Studies* 32, 228–265.

Cheng, Ing-Haw, 2019, The VIX premium, *Review of Financial Studies* 32, 180–227.

Cheng, Ing-Haw, 2020, Volatility markets underreacted to the early stages of the COVID-19 pandemic, *Review of Asset Pricing Studies* 10, 635–668.

Cohen, Lauren, Karl B Diether, and Christopher J Malloy, 2007, Supply and demand shifts in the shorting market, *Journal of Finance* 62, 2061–2096.

Crescini, Alessandro, Fabio Trojani, and Andrea Vedolin, 2025, Demand-based expected returns, *Working Paper*.

Dew-Becker, Ian, Stefano Giglio, Anh Le, and Marius Rodriguez, 2017, The price of variance risk, *Journal of Financial Economics* 123, 225–250.

Dim, Chukwuma, Bjorn Eraker, and Grigory Vilkov, 2023, 0dtes: Trading, gamma risk and volatility propagation, *Working Paper*.

Eraker, Bjørn, and Yue Wu, 2017, Explaining the negative returns to volatility claims: An equilibrium approach, *Journal of Financial Economics* 125, 72–98.

Eraker, Bjørn, and Aoxiang Yang, 2022, The price of higher order catastrophe insurance: The case of VIX options, *Journal of Finance* 77, 3289–3337.

Farago, Adam, Mariana Khapko, and Chayawat Ornthanalai, 2021, Asymmetries and the market for put options, *Working Paper, University of Toronto*.

Faust, Jon, 1998, The robustness of identified VAR conclusions about money, *Carnegie-Rochester Conference Series on Public Policy* 49, 207–244.

Fontaine, Jean-Sebastien, René Garcia, and Sermin Gungor, 2023, Intermediary leverage shocks and funding conditions, *Journal of Finance*.

Fournier, Mathieu, and Kris Jacobs, 2020, A tractable framework for option pricing with dynamic market maker inventory and wealth, *Journal of Financial and Quantitative Analysis* 55, 1117–1162.

Gabaix, Xavier, and Ralph SJ Koijen, 2021, In search of the origins of financial fluctuations: The inelastic markets hypothesis, *Working Paper, NBER*.

Gârleanu, Nicolae, Lasse Heje Pedersen, and Allen M Poteshman, 2009, Demand-based option pricing, *Review of Financial Studies* 22, 4259–4299.

Ghaderi, Mohammad, Mete Kilic, and Sang Byung Seo, 2024, Why do rational investors like variance at the peak of a crisis? A learning-based explanation, *Journal of Monetary Economics* 142, 103513.

Goldberg, Jonathan, and Yoshio Nozawa, 2021, Liquidity supply in the corporate bond market, *Journal of Finance* 76, 755–796.

Gu, Chen, Xu Guo, Alexander Kurov, and Raluca Stan, 2022, The information content of the volatility index options trading volume, *Journal of Futures Markets* 42, 1721–1737.

Heston, Steven L, 1993, A closed-form solution for options with stochastic volatility with applications to bond and currency options, *Review of Financial Studies* 6, 327–343.

Holowczak, Richard, Jianfeng Hu, and Liuren Wu, 2014, Aggregating information in option transactions, *Journal of Derivatives* 21, 9.

Hu, Guanglian, and Rui Liu, 2024, Short term VIX futures, *Working Paper*.

Huang, Darien, Christian Schlag, Ivan Shaliastovich, and Julian Thimme, 2019, Volatility-of-volatility risk, *Journal of Financial and Quantitative Analysis* 54, 2423–2452.

Jacobs, Kris, and Anh Thu Mai, 2024, The role of intermediaries in derivatives markets: Evidence from VIX options, *Journal of Empirical Finance* 77, 101492.

Jacobs, Kris, Anh Thu Mai, and Paola Pederzoli, 2024, Identifying demand curves in index option markets, *Management Science (Forthcoming)*.

Johnson, Travis L, 2017, Risk premia and the vix term structure, *Journal of Financial and Quantitative Analysis* 52, 2461–2490.

Kilian, Lutz, 2009, Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market, *American Economic Review* 99, 1053–1069.

Kilian, Lutz, and Helmut Lütkepohl, 2017, Structural vector autoregressive analysis, *Cambridge University Press*.

Koijen, Ralph SJ, Robert J Richmond, and Motohiro Yogo, 2020, Which investors matter for equity valuations and expected returns?, *Working Paper, NBER*.

Koijen, Ralph SJ, and Motohiro Yogo, 2019, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.

Lin, Yueh-Neng, and Chien-Hung Chang, 2009, VIX option pricing, *Journal of Futures Markets* 29, 523–543.

Lochstoer, Lars A, and Tyler Muir, 2022, Volatility expectations and returns, *Journal of Finance* 77, 1055–1096.

Lütkepohl, Helmut, 2005, *New introduction to multiple time series analysis*. (Springer Science & Business Media).

Mencia, Javier, and Enrique Sentana, 2013, Valuation of VIX derivatives, *Journal of Financial Economics* 108, 367–391.

Muravyev, Dmitriy, 2016, Order flow and expected option returns, *Journal of Finance* 71, 673–708.

Ni, Sophie X, Neil D Pearson, Allen M Poteshman, and Joshua White, 2021, Does option trading have a pervasive impact on underlying stock prices?, *The Review of Financial Studies* 34, 1952–1986.

Ober, Alexander, 2025, Intermediary Risk and the Pricing Kernel, *Working Paper*.

Park, Yang-Ho, 2015, Volatility-of-volatility and tail risk hedging returns, *Journal of Financial Markets* 26, 38–63.

Terstegge, Julian, 2025, Intermediary Option Pricing, *Working Paper*.

Tong, Chen, Zhuo Huang, and Tianyi Wang, 2022, Do VIX futures contribute to the valuation of VIX options?, *Journal of Futures Markets* 42, 1644–1664.

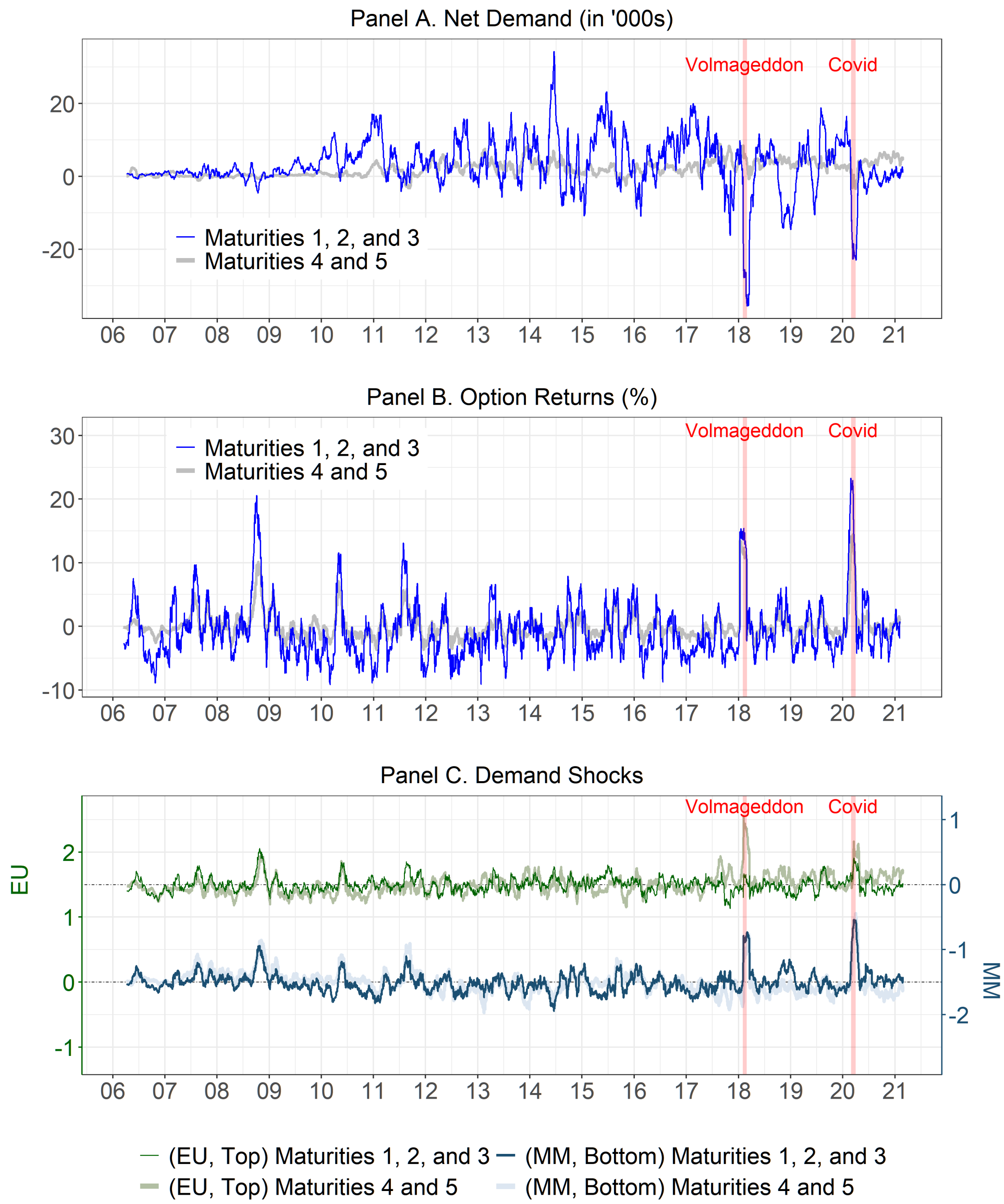
Uhlig, Harald, 2005, What are the effects of monetary policy on output? Results from an agnostic identification procedure, *Journal of Monetary Economics* 52, 381–419.

Wang, Tianyi, Yiwen Shen, Yueting Jiang, and Zhuo Huang, 2017, Pricing the CBOE VIX futures with the Heston–Nandi GARCH model, *Journal of Futures Markets* 37, 641–659.

Zhang, Jin E, and Yingzi Zhu, 2006, VIX futures, *Journal of Futures Markets* 26, 521–531.

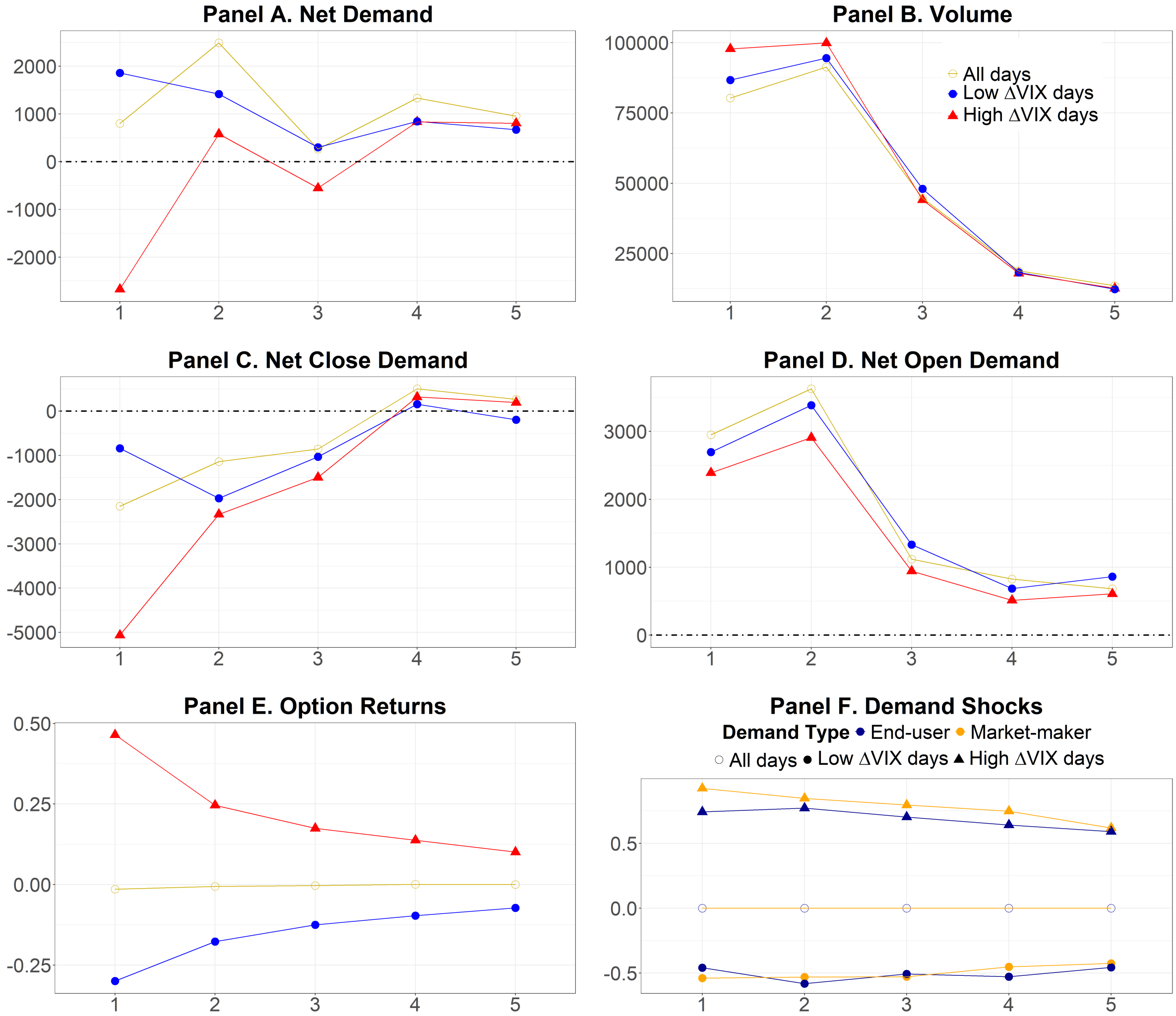
Zhu, Song-Ping, and Guang-Hua Lian, 2012, An analytical formula for VIX futures and its applications, *Journal of Futures Markets* 32, 166–190.

Figure 1: Time Series of Net Demand, Option Returns, and Demand Shocks



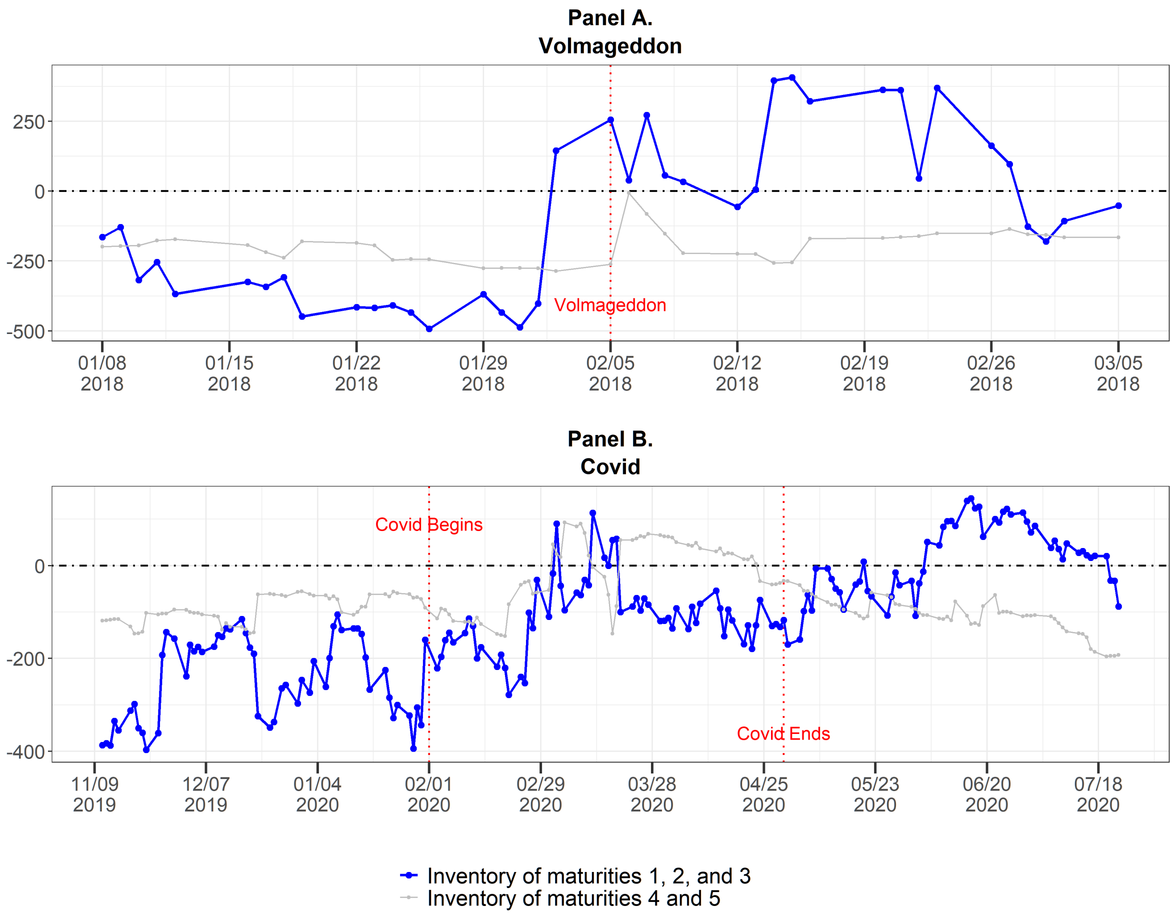
This figure displays the time series of the thirty-day moving average of daily net demand (Panel A), option returns (Panel B), and the estimated demand shocks (Panel C) for short- and long-maturity VIX call options. Short-maturity options are defined as those with less than three months to expiration (categories 1, 2, and 3), while long-maturity options have maturities between three and twelve months (categories 4 and 5). The figure also highlights two significant events: the Volmageddon in February 2018 and the onset of the COVID-19 crisis in February 2020.

Figure 2: The Term Structure on High and Low ΔVIX Days



This figure shows the conditional term structure of net demand (Panel A), volume (Panel B), net close demand (Panel C), net open demand (Panel D), and option returns (Panel E) on high-risk and low-risk days. High (low) risk days are identified as those within the top (bottom) quintile of ΔVIX_t. Panel F plots a similar term structure for market-maker (MM) and end-user (EU) demand shocks.

Figure 3: The Time Series of Inventory in Two High-Risk Periods



This figure plots daily inventory positions for market makers in VIX call options with short maturities (under three months) and long maturities (four to twelve months) during the Volmageddon (Panel A) and COVID-19 (Panel B) crises. Daily inventory is measured as the negative of cumulative net demand from firms and customers, aggregated by maturity categories. The time series spans four weeks around the Volmageddon event, from January 08, 2018 to March 05, 2018, and twelve weeks before and after the COVID-19 crisis, from November 09, 2019 to July 18, 2020.

Table 1: Summary Statistics

Panel A. VIX Call Net Demand

Maturity	*1*	*2*	*3*	*4*	*5*
Mean	801*	2487***	265	1331***	953***
t-stat	[2.44]	[6.23]	[1.39]	[11.01]	[8.85]
Std	16430	17523	10520	6625	4597
Skew	-2.84	-1.35	-7.76	1.75	-0.50
Kurt	45.11	67.16	190.43	55.62	38.20
# Obs	3567	3578	3520	3410	3759
# Series	7774	8355	4421	4174	4387

Panel B. VIX Call Volume

Maturity	*1*	*2*	*3*	*4*	*5*
Mean	80326***	91339***	44713***	18848***	13550***
t-stat	[17.79]	[16.76]	[17.05]	[15.87]	[13.96]
Std	98292	118269	79607	42134	29077
Skew	3.21	3.62	6.02	7.44	7.08
Kurt	16.39	22.86	55.92	84.24	88.41
# Obs	3567	3578	3520	3410	3759
# Series	7774	8355	4421	4174	4387

Panel C. VIX Call Returns

Maturity	*1*	*2*	*3*	*4*	*5*
Mean	-1.43%*	-0.57%.	-0.29%	0.06%	0.04%
t-stat	[-2.22]	[-1.71]	[-1.07]	[0.28]	[0.2]
Std	0.37	0.20	0.15	0.13	0.11
Skew	3.88	3.84	6.32	8.59	14.53
Kurt	40.64	47.03	133.46	222.24	507.43
# Obs	3567	3578	3520	3410	3759
# Series	7774	8355	4421	4174	4387

Panel D. VIX Futures Returns

Maturity	*1*	*2*	*3*	*4*	*5*
Mean	-0.14%	-0.08%	-0.06%	-0.02%	-0.01%
t-stat	[-1.58]	[-1.29]	[-1.14]	[-0.39]	[-0.22]
Std	0.05	0.04	0.03	0.03	0.02
Skew	2.64	2.43	3.29	2.12	1.35
Kurt	30.02	28.96	53.71	20.67	11.39
# Obs	3661	3584	3523	3493	3777
# Series	408	405	177	175	180

This table displays summary statistics for daily VIX call net demand (Panel A), VIX call volume (Panel B), VIX call returns (Panel C), and VIX futures returns (Panel D) for different maturities. The five maturity categories are defined as follows: one month or less (category 1), one to two months (category 2), two to three months (category 3), three to four months (category 4), and four to twelve months (category 5). ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table 2: Differences in Net Demand, Returns, and Latent Demand on High-Risk and Low-Risk Days

Panel A: High vs. Low Risk Days

	ΔVIX_H-ΔVIX_L					$VVIX_H$-$VVIX_L$				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
Net Demand	-4534***	-836	-922.	-30	138	-4989***	-5608***	-2755***	229	213
Volume	11182.	5367	-4229	-360	340	30000***	40186***	8546*	3017	4034*
Net Close Demand	-4231***	-359	-502	140	394	-3721***	-4260***	-2090***	515	-616*
Net Open Demand	-303	-476	-421	-170	-257	-1267*	-1347	-664	-287	829**
Option Returns	0.76***	0.42***	0.30***	0.23***	0.17***	0.25***	0.13***	0.10***	0.07***	0.06***
MM Shocks	1.46***	1.37***	1.32***	1.19***	1.04***	0.55***	0.54***	0.54***	0.35***	0.27***
EU Shocks	1.20***	1.35***	1.20***	1.16***	1.04***	0.31***	0.28***	0.26***	0.40***	0.39***

Panel B. MM vs. EU Demand Shocks on High-Risk Days

	ΔVIX_H					$VVIX_H$				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
MM Shocks	0.92***	0.84***	0.79***	0.74***	0.61***	0.36***	0.40***	0.38***	0.24***	0.20***
EU Shocks	0.74***	0.77***	0.69***	0.63***	0.59***	0.24***	0.16**	0.18***	0.27***	0.26***
Diff	0.18**	0.07	0.10.	0.11.	0.03	0.12.	0.23**	0.19**	-0.03	-0.06

Panel A reports differences between high- and low-risk days in VIX call net demand, trading volume, net demand for opening and closing positions, option returns, and market-maker (MM) and end-user (EU) demand shocks. Panel B displays the average values of MM demand shocks, EU demand shocks, and their differences on high-risk days. High- (low-) risk days are defined as those in the top (bottom) quintile of daily changes in the VIX index (ΔVIX) or the level of VVIX. ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table 3: Forecast Error Variance Decomposition (FEVD) of Net Demand

Maturity	***1***	***2***	***3***	***4***	***5***
Panel A. Full sample	-7.48	-4.32	-0.54	1.00	0.39
Panel B. During Volatility Events					
Flash Crash (Aug 17, 2015 - Oct 24, 2015)	-41.58	-8.25	-22.17	-4.75	-7.29
Volmageddon (Jan 29, 2018 - Apr 05, 2018)	-15.91	-29.78	-3.95	-43.58	-8.70
Panel C. During Crises					
Sep 22, 2008 - Nov 22, 2008	-13.17	20.43	3.40	2.46	5.86
Feb 16, 2020 - Apr 16, 2020	-11.96	-14.89	1.37	26.56	-11.56

This table reports the difference between the one-step ahead forecast error variance decomposition (FEVD) of net demand attributable to end-user demand versus that attributable to market-maker demand. We present results for the full sample estimation (Panel A) and for the estimation of the demand system using four subsamples (Panels B and C). Specifically, Panel B reports results for two major volatility events, with each window spanning from one week before the event date to two months after: (i) Flash Crash, August 17 – October 24, 2015 (event date: August 24, 2015), and (ii) Volmageddon, January 29 – April 5, 2018 (event date: February 5, 2018). Panel C reports results for two crisis periods: (i) September 22 –November 22, 2008 (financial crisis peak) and (ii) February 16 – April 16, 2020 (Covid crisis peak).

Table 4: The Determinants of Demand Shocks

	MM Demand Shocks					EU Demand Shocks				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
$E_t[R_{VIX,t+1}]$	30.32***	15.86**	15.34.	14.46*	5.73	4.76	0.38	-1.23	1.07	-1.00
	[4.83]	[2.58]	[1.86]	[2.01]	[0.80]	[0.87]	[0.05]	[-0.21]	[0.15]	[-0.18]
R^2	1.13	0.31	0.29	0.25	0.02	0.01	-0.03	-0.03	-0.03	-0.03
ΔInv Risk$_{t-1}$	199.69	-324.34***	277.98.	300.43	-12.32	180.39	86.24	-58.43	-331.49	-37.12
	[1.54]	[-4.18]	[1.90]	[0.89]	[-0.03]	[1.29]	[0.63]	[-0.36]	[-1.25]	[-0.06]
R^2	0.14	0.42	0.07	0.01	-0.03	0.11	0.01	-0.03	0.02	-0.03
ΔWealth$_{t-1}$	-0.06	-0.07***	0.40.	-0.50*	-0.15**	0.07	0.02***	0.26	0.48	0.22***
	[-0.30]	[-19.79]	[1.80]	[-2.46]	[-3.21]	[0.40]	[5.44]	[1.40]	[0.95]	[5.45]
R^2	-0.03	0.51	0.24	0.38	0.20	-0.02	0.01	0.08	0.36	0.46

This table presents results from regressing market-maker or end-user demand shocks on the following variables: i) the expected return on a long VIX future position ($E_t[r_{VIX,T}]$), as calculated in Cheng (2019), ii) lagged changes in inventory risk (ΔInv Risk$_{t-1}$ [scaled by 10,000]), and iii) lagged changes in market-maker wealth (ΔWealth$_{t-1}$ [scaled by 100,000]). The regressions are performed separately for each option maturity category and standard errors are calculated using Newey-West correction with twenty lags. ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table 5: The Term Structure of the Bid-Ask Spread

Panel A. Bid-Ask Spreads: Summary Statistics

Maturity	***1***	***2***	***3***	***4***	***5***
Mean	0.36	0.26	0.20	0.22	0.27
Std	0.61	0.45	0.19	0.19	0.23
Skewness	8.40	13.50	19.86	11.52	9.97
Kurtosis	103.66	254.89	652.37	258.22	245.58

Panel B. Average Spread Difference on High vs. Low Risk Days

Maturity	***1***	***2***	***3***	***4***	***5***
ΔVIX_H - ΔVIX_L	0.04	0.00	0.02	0.01	0.01
$VVIX_H$ - $VVIX_L$	0.75***	0.33***	0.05***	0.04**	0.04*

Panel C. Regressing $\Delta Spread_t$ on the Demand Shocks

Maturity	***1***	***2***	***3***	***4***	***5***
MM shocks	7.17***	7.49.	6.02	5.71.	7.39*
t-stat	[3.46]	[1.78]	[1.51]	[1.69]	[1.98]
R^2	3.50	3.90	7.83	10.64	13.68
EU shocks	5.35*	4.68**	5.66	4.60.	7.34.
t-stat	[2.35]	[2.91]	[1.47]	[1.65]	[1.67]
R^2	1.91	1.50	6.95	6.86	13.44

Panel A presents summary statistics for the term structure of the dollar spreads. Panel B shows the difference in average spreads between high- and low-risk variable days. High- and low-risk days are identified using the top (bottom) quintile of ΔVIX or VVIX. Panel C shows the results of univariate regressions of $\Delta Spread_t$ on market maker (MM) or end user (EU) demand shocks. The coefficients are multiplied by 100 and standard errors are calculated using Newey-West correction with 20 lags. ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table 6: Alternative Risk Measures

Panel A. High vs. Low Risk Days

	VIX_H - VIX_L					$\Delta Skew_L$ - $\Delta Skew_H$					$r_{S\&P500,L}$ - $r_{S\&P500,H}$				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
Net Demand	-2669**	-6203***	-2363**	-1528***	-1685***	-4295***	-464	-499	-448	288	-4516***	-1555	-1373**	-588	-112
Net Close Dem	391	-1647.	-1798***	-966**	-1996***	-4177***	-721	-411	-382	64	-3555***	-1737.	-825.	-157	81
Net Open Dem	-3060***	-4556***	-565	-562.	311	-117	256	-89	-66	225	-961	182	-548	-432	-193
Option Ret	0.17***	0.09***	0.06***	0.05***	0.04***	0.68***	0.37***	0.26***	0.21***	0.15***	0.73***	0.40***	0.29***	0.23***	0.17***
MM Shocks	0.34***	0.43***	0.40***	0.40***	0.40***	1.29***	1.19***	1.15***	1.10***	0.89***	1.38***	1.32***	1.31***	1.22***	1.04***
EU Shocks	0.24***	0.12*	0.15**	0.11*	0.04	1.06***	1.19***	1.08***	1.00***	0.95***	1.14***	1.27***	1.14***	1.08***	1.00***
Spread	0.46***	0.31***	0.20***	0.26***	0.31***	0.01	0.01	0.02	0.01	0.02	0.08.	0.08*	0.04**	0.03*	0.05**

Panel B. MM vs. EU Demand Shocks on High-Risk Days

	VIX_H					$\Delta Skew_L$					$r_{S\&P500,L}$				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
MM Shocks	0.18***	0.19***	0.23***	0.24***	0.23***	0.85***	0.76***	0.72***	0.69***	0.57***	0.87***	0.82***	0.79***	0.75***	0.63***
EU Shocks	0.11**	0.12**	0.09*	0.08.	0.06	0.66***	0.68***	0.63***	0.56***	0.53***	0.71***	0.73***	0.65***	0.60***	0.54***
Diff	0.06	0.08	0.14*	0.15*	0.18**	0.19**	0.09	0.1	0.14*	0.05	0.16*	0.09	0.14*	0.15*	0.09

This table presents robustness results using different measures of risk: i) the level of the VIX index (VIX), ii) daily changes in unstandardized risk-neutral skewness (ΔSkew) computed using the methodology of Bakshi and Kapadia (2003), and iii) S&P 500 daily returns ($r_{S\&P500}$). Panel A reports differences in VIX call net demand, option returns, net demand for opening and closing positions, market-maker (MM) and end-user (EU) demand shocks, and bid-ask spread between high- and low-risk days. Panel B displays the average values of MM demand shocks, EU demand shocks, and their differences on high-risk days, respectively. ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table 7: Results by Option Moneyness

Panel A. Summary Statistics of Net Demand

	OTM Calls					ATM Calls					ITM Calls				
Maturity	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*
Mean	1313	1158	-217	338	423	99	1280	383	643	200	-270	38	91	43	212
Std	14624	18194	15091	7009	4320	9390	11442	8730	5644	2892	5393	4143	3318	1833	1491
Skewness	-3.65	-8.71	-18.57	-3.43	-1.11	-1.09	4.41	10.90	9.92	2.09	-0.95	-2.67	3.62	14.67	3.98
Kurtosis	80.08	319.93	641.74	99.21	55.05	20.68	124.5	387.89	177.98	37.45	40.4	36.86	259.96	408.46	89.04

Panel B. Average Net Demand Difference on High vs. Low Risk Days

	OTM Calls					ATM Calls					ITM Calls				
Maturity	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*
ΔVIX_H - ΔVIX_L	180	-1568	-437	255	74	-2484***	1045	-265	157	148	-1803***	-201	-31	-188.	-94
$VVIX_H$ - $VVIX_L$	-514	-1179	-486	-500	444.	-1851***	-2622***	-1102*	-151	-370*	-1883***	-1745***	-986***	-60	41

Panel C. MM vs. EU Demand Shocks on High-Risk Days

Maturity	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*	*1*	*2*	*3*	*4*	*5*
	OTM Calls ΔVIX_H					**ATM Calls ΔVIX_H**					**ITM Calls ΔVIX_H**				
MM shocks	0.80***	0.80***	0.73***	0.68***	0.58***	0.92***	0.82***	0.81***	0.77***	0.70***	0.93***	0.86***	0.88***	0.89***	0.82***
EU shocks	0.82***	0.75***	0.72***	0.65***	0.56***	0.68***	0.81***	0.76***	0.71***	0.72***	0.76***	0.78***	0.73***	0.71***	0.72***
Diff	-0.02	0.05	0.01	0.03	0.02	0.24***	0.01	0.05	0.06	-0.02	0.17**	0.08	0.15**	0.18***	0.10*
	OTM Calls $VVIX_H$					**ATM Calls $VVIX_H$**					**ITM Calls $VVIX_H$**				
MM shocks	0.40***	0.34***	0.29***	0.27***	0.19***	0.33***	0.38***	0.33***	0.31***	0.30***	0.36***	0.40***	0.39***	0.31***	0.27***
EU shocks	0.35***	0.25***	0.24***	0.24***	0.25***	0.31***	0.22***	0.24***	0.24***	0.24***	0.23***	0.18**	0.21***	0.25***	0.29***
Diff	0.05	0.09	0.05	0.03	-0.06	0.02	0.15*	0.08	0.06	0.06	0.13.	0.22**	0.18*	0.07	-0.01

This table reports summary statistics for net demands (Panel A), the difference in average net demands between high and low risk days (Panel B), and the average value of MM demand shocks, EU demand shocks, and their difference on high-risk days, identified as the top quintile of ΔVIX or VVIX (Panel C). We present results separately for out-of-the-money (OTM), at-the-money (ATM), and in-the-money (ITM) VIX call options. Options are defined OTM if $0.125 < \Delta \leq 0.375$, ATM if $0.375 < \Delta \leq 0.625$, and ITM if $0.625 < \Delta \leq 0.875$. ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table 8: Alternative Definitions of Net Demand

Panel A. Summary Statistics of Net Demand

	ND2					ND3				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
Mean	-128.39	944.33	296.74	470.88	365.39	0.01	0.04	0.01	0.11	0.15
Std	7676.62	6306.4	3554.98	2678.5	1804.68	0.22	0.22	0.30	0.42	0.4
Skewness	-4.32	-0.48	-0.37	5.38	0.30	-0.07	0.45	0.01	-0.05	-0.09
Kurtosis	53.09	44.62	76.00	84.44	52.47	5.79	6.45	4.53	2.85	2.88

Panel B. Average Net Demand Difference on High vs. Low Risk Days

	ND2					ND3				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
ΔVIX_H - ΔVIX_L	-3219***	182	-264	-39	25	-0.06***	-0.02.	-0.02	-0.07**	-0.06**
$VVIX_H$ - $VVIX_L$	-3174***	-3065***	-1504***	-177	-55	-0.04**	-0.02.	-0.06***	-0.03	-0.13***

Panel C. MM vs. EU Demand Shock on High-Risk Days

Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
	ND2 ΔVIX_H					**ND3 ΔVIX_H**				
MM shock	0.99***	0.84***	0.81***	0.77***	0.64***	0.90***	0.87***	0.78***	0.75***	0.68***
EU shock	0.69***	0.78***	0.66***	0.61***	0.57***	0.77***	0.74***	0.70***	0.63***	0.52***
Diff	0.30***	0.05	0.15*	0.15*	0.07	0.13*	0.13*	0.08	0.12.	0.16*
	ND2 $VVIX_H$					**ND3 $VVIX_H$**				
MM shock	0.37***	0.43***	0.37***	0.30***	0.22***	0.33***	0.33***	0.31***	0.24***	0.29***
EU shock	0.23***	0.17***	0.18***	0.22***	0.25***	0.29***	0.25***	0.24***	0.27***	0.18***
Diff	0.14.	0.26***	0.19*	0.08	-0.03	0.04	0.08	0.07	-0.03	0.11

This table reports results for the alternative net demand measures $ND2$ and $ND3$. Panel A presents summary statistics of these net demands. Panel B presents the difference in average net demands between high-risk and low-risk days. Panel C presents the average value of the MM demand shocks, EU demand shocks, and their differences on high-risk days, identified as the top quintile of ΔVIX or VVIX (Panel C). ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table 9: Modeling the Underlying VIX

MM vs. EU Demand Shocks on High-Risk Days

	Panel A. VAR with Δ-Hedged Returns					**Panel B. Extended VAR with ΔVIX**				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
			$\mathbf{VVIX}_H$					$\mathbf{VVIX}_H$		
MM shocks	0.31***	0.31***	0.23***	0.07	0.04	0.31***	0.36***	0.34***	0.22***	0.16**
EU shocks	0.14**	0.03	0.00	0.08	0.08	0.22***	0.20***	0.18***	0.24***	0.22***
Diff	0.18*	0.28***	0.23**	-0.01	-0.04	0.09	0.16*	0.17**	-0.02	-0.05
			$r_{S\&P500,L}$					$r_{S\&P500,L}$		
MM shocks	0.44***	0.38***	0.30***	0.21***	0.12*	0.63***	0.60***	0.57***	0.52***	0.41***
EU shocks	0.19***	0.21***	0.13**	0.05	0.03	0.53***	0.55***	0.45***	0.40***	0.33***
Diff	0.25***	0.17*	0.17**	0.16*	0.09	0.11.	0.05	0.12*	0.12.	0.08

Panel A and B present the average value of the market-maker (MM) demand shocks, end-user (EU) demand shocks, and their differences on high-risk days, defined as the top quintile of VVIX or the bottom quintile of S&P 500 returns. In Panel A, the shocks are estimated using delta-hedged returns as price variable and baseline net demand as the quantity variable. In Panel B, the shocks are estimated with an extended VAR which includes ΔVIX alongside the baseline price and quantity variables. ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table 10: Identifying Systematic Demand Factors

Panel A: Systematic Shocks in High-Risk Days

	Δ**VIX$_H$**	**VVIX$_H$**
MM shocks	0.89***	0.38***
EU shocks	0.72***	0.21***
Diff	0.17**	0.17*

Panel B: Regressing Demand on Systematic Shocks

	Market-Maker Demand Shocks				
Maturity	***1***	***2***	***3***	***4***	***5***
Sys MM Shocks$_t$	0.74***	0.79***	0.71***	0.59***	0.52***
	[13.62]	[14.85]	[15.62]	[12.59]	[8.81]
R^2	57.16	64.97	53.85	38.19	28.21

	End-User Demand Shocks				
Maturity	***1***	***2***	***3***	***4***	***5***
Sys EU Shocks$_t$	0.70***	0.73***	0.66***	0.52***	0.47***
	[21.61]	[13.32]	[14.22]	[9.55]	[8.04]
R^2	49.98	55.66	46.65	29.74	23.13

Panel A reports differences in market-maker (MM) and end-user (EU) systematic demand shocks between high- and low-risk days. The systematic demand shocks are estimated from the demand system using the combined sample of VIX call options comprising all maturities. Panel B presents the results obtained by regressing MM shocks or EU shocks on the MM or EU systematic demand shocks. The regressions are performed separately for each option maturity category. Standard errors are calculated using Newey-West correction with twenty lags. ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

APPENDIX

A Identifying the Demand Curves Using Sign-Restricted VARs

This section outlines the framework we use to identify end users' and market makers' demand equations in the VIX call option market:

$$\begin{cases} P_{MM,t} & = \beta_{MM} Q_{MM,t} + \varepsilon_{MM,t} \\ P_{EU,t} & = \beta_{EU} Q_{EU,t} + \varepsilon_{EU,t} \end{cases} \tag{A.1}$$

Here, P_t and Q_t respectively denote the equilibrium option price ($P_t = P_{MM,t} = P_{EU,t}$) and quantity traded by either market makers (MM) or end users (EU). The zero net supply in the option market requires that $Q_{MM,t} + Q_{EU,t} = 0$. We simplify notation by representing the end-user quantity as $Q_t = Q_{EU,t} = -Q_{MM,t}$.

Our approach employs the pure-sign restriction vector autoregression (Uhlig, 2005) to identify demand shocks, $\varepsilon_{MM,t}$ and $\varepsilon_{EU,t}$.

Let $y_t = (P_t \quad Q_t)'$ represent the stacked vector of endogenous prices and quantities in the reduced-form ℓ-lag VAR:

$$Y_t = \alpha + \sum_{i=1}^{l} B_i Y_{t-i} + u_t \tag{A.2}$$

where u_t is the reduced-form residual, a (2×1) vector with covariance matrix $E[u_t u_t'] = \Sigma$. B_i is a (2×2) matrix of coefficients, for $i \in (1, ..., \ell)$, and α is a (2×1) vector of constants. This forms a system of two equations with price and quantity as the endogenous variables–a reduced-form of the system in Equation (A.1). To identify the market makers' and end users' demand equations, we decompose the residuals u_t into orthonormal structural or fundamental shocks. The mapping from these orthonormal fundamental shocks ε_t, with $E[\varepsilon_t \varepsilon_t'] = I$, to the residual u_t is through the matrix **A**, as follows:

$$u_t = \mathbf{A}\varepsilon_t \Rightarrow \Sigma = E[u_t u_t'] = \mathbf{A}E[\varepsilon_t \varepsilon_t']\mathbf{A'} = \mathbf{AA'}. \tag{A.3}$$

Identifying structural shocks is equivalent to identifying the impact matrix **A**. To distinguish the first equation as the market-maker demand equation and the second as the end-user demand equation, the pure-sign restriction approach imposes specific sign restrictions on the elements of matrix **A**:

$$\begin{bmatrix} u_t^P \\ u_t^Q \end{bmatrix} = A \begin{bmatrix} \varepsilon_{MM,t} \\ \varepsilon_{EU,t} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{MM,t} \\ \varepsilon_{EU,t} \end{bmatrix} = \begin{bmatrix} + & + \\ - & + \end{bmatrix} \begin{bmatrix} \varepsilon_{MM,t} \\ \varepsilon_{EU,t} \end{bmatrix} \tag{A.4}$$

The columns of matrix **A** demonstrate the impact of each demand shock on prices and quantities: when both end users and market makers experience positive shocks, prices rise, but end users' quantity traded (Q_t) moves in opposing directions. These sign patterns are essential for identifying shocks in the structural VAR framework, as noted by Kilian and Lütkepohl (2017). The resulting restrictions are basic, reflecting core economic intuition about demand curves in a zero net-supply context.

Once we identify the impact matrix **A**, we can recover the structural shocks $\varepsilon_t = \mathbf{A}^{-1}u_t$. However, the admissible matrix **A** is not unique; the estimation of the shocks and the coefficients of the system is based on the average of the estimates obtained for all admissible matrices **A**.

We implement the estimation of the pure-sign restricted VAR using a Bayesian approach, following Uhlig (2005). This approach can be summarized in six steps. First, we estimate the reduced-form VAR(ℓ) using ordinary least squares (OLS), where the optimal number of lags ℓ is chosen based on Bayesian Information Criterion (BIC):

$$\begin{bmatrix} P_t \\ Q_t \end{bmatrix} = \begin{bmatrix} \alpha^{MM} \\ \alpha^{EU} \end{bmatrix} + \sum_{i=1}^{l} \begin{bmatrix} b^P_{MM,i} & b^Q_{MM,i} \\ b^P_{EU,i} & b^Q_{EU,i} \end{bmatrix} \begin{bmatrix} P_{t-i} \\ Q_{t-i} \end{bmatrix} + \begin{bmatrix} u_t^{MM} \\ u_t^{EU} \end{bmatrix} \tag{A.5}$$

Second, we assume a diffusive conjugate Normal-Wishart prior for $(\mathbf{B},\mathbf{\Sigma})$, where $\mathbf{B} = [\alpha, B_1, ..., B_l]$, and draw 100 samples from the posterior over $\mathbf{B}$ and $\mathbf{\Sigma}$. Third, for each sample of $\mathbf{\Sigma}$, we draw 1,000 samples of an orthonormal matrix $\mathbf{Q}$ uniformly from the unit circle using QR factorization. Fourth, we compute the candidate impact matrix $\mathbf{A_m} = \mathbf{LQ}$, where $\mathbf{L}$ is the lower triangular Cholesky decomposition for each sample of $\mathbf{\Sigma}$.[36] We then verify if $\mathbf{A_m}$ satisfies the sign restrictions of Equation (A.4) and discard any samples that violate the sign restrictions. Fifth, for each retained $\mathbf{A_m}$, we recover the structural shocks $\varepsilon_t = \mathbf{A_m}^{-1} u_t$ and finally, in the sixth step of the estimation procedure, we calculate the mean of the shocks from the retained draws.

Other Supplementary Figures and Tables

[Figure A.1 about here.]

[Figure A.2 about here.]

[Figure A.3 about here.]

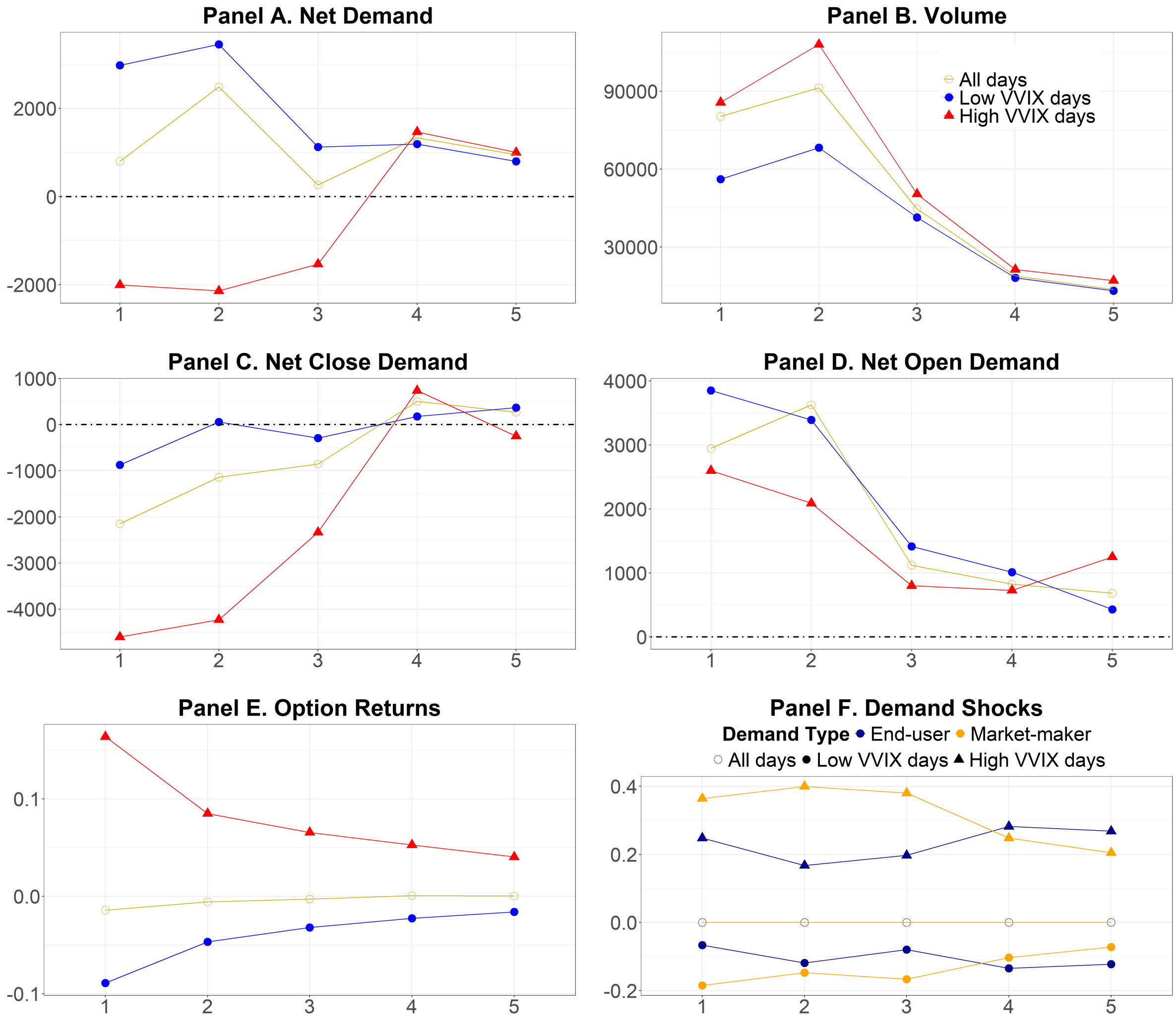
[Table A.1 about here.]

[Table A.2 about here.]

[Table A.3 about here.]

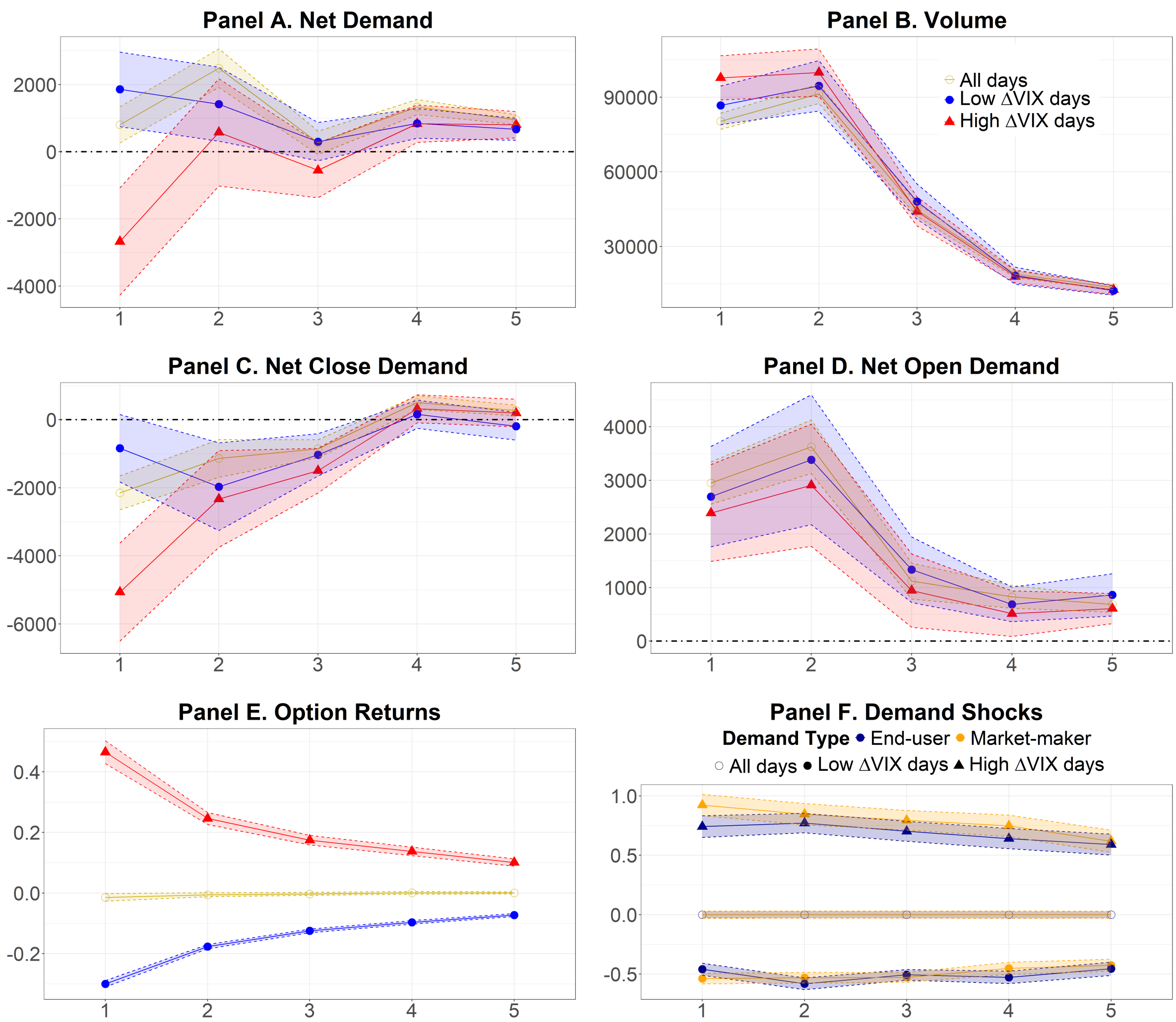
[36]Note that any matrix $\mathbf{A}$ such that $\Sigma = \mathbf{AA'}$ can be expressed as a permutation of the Cholesky matrix through an orthonormal matrix $\mathbf{Q}$: $\mathbf{A} = \mathbf{LQ}$.

Figure A.1: The Conditional Term Structures on High and Low VVIX Days



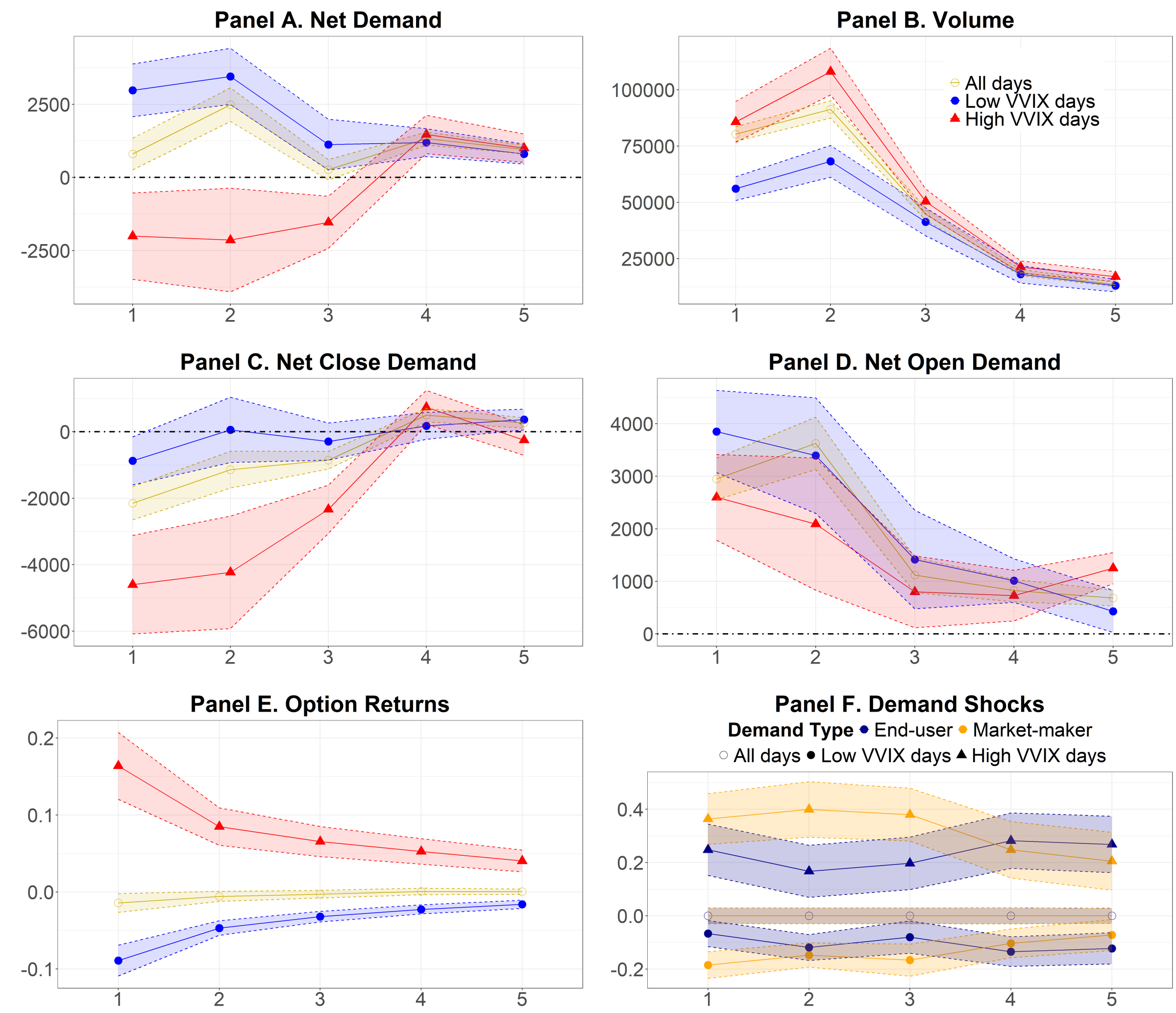
This figure shows the conditional term structure of net demand (Panel A), volume (Panel B), net close demand (Panel C), net open demand (Panel D), and option returns (Panel E) on high-risk and low-risk days. Panel F plots a similar term structure for market-maker (MM) and end-user (EU) demand shocks. High (low) risk days are identified as those within the top (bottom) quintile of $VVIX_t$.

Figure A.2: The Conditional Term Structure on High and Low ΔVIX Days, Including 95% Confidence Intervals



This figure shows the conditional term structure of net demand (Panel A), volume (Panel B), net close demand (Panel C), net open demand (Panel D), and option returns (Panel E) on high-risk and low-risk days, along with 95% confidence intervals. Panel F plots a similar term structure for market-maker (MM) and end-user (EU) demand shocks. High (low) risk days are identified as those within the top (bottom) quintile of ΔVIX_t.

Figure A.3: The Conditional Term Structure on High and Low VVIX Days, Including 95% Confidence Intervals



This figure shows the conditional term structure of net demand (Panel A), volume (Panel B), net close demand (Panel C), net open demand (Panel D), and option returns (Panel E) on high-risk and low-risk days, along with 95% confidence intervals. Panel F plots a similar term structure for market-maker (MM) and end-user (EU) demand shocks. High (low) risk days are identified as those within the top (bottom) quintile of $VVIX_t$.

Table A.1: Results for VIX Put Options

Panel A. Summary Statistics of Net Demand

Maturity	*1*	*2*	*3*	*4*	*5*
Mean	-323.51	-1593.41	-398.5	-97.01	53.38
Std	15338.12	12297.21	8429.38	3233.86	2906.19
Skewness	5.26	-7.60	-13.35	-0.74	-1.02
Kurtosis	99.32	162.02	411.24	23.74	38.54

Panel B. Average Net Demand Difference on High vs. Low Risk Days

Maturity	*1*	*2*	*3*	*4*	*5*
ΔVIX$_H$ - ΔVIX$_L$	8636***	1485*	677*	430*	439**
VVIX$_H$ - VVIX$_L$	3195***	2554***	355	301	228

Panel C. MM vs. EU Demand Shocks on High-Risk Days

Maturity	*1*	*2*	*3*	*4*	*5*
			ΔVIX$_H$		
MM shocks	-0.89***	-0.82***	-0.78***	-0.78***	-0.76***
EU shocks	-0.63***	-0.71***	-0.70***	-0.65***	-0.63***
Diff	-0.26***	-0.11*	-0.08*	-0.14**	-0.12**
			VVIX$_H$		
MM shocks	-0.28***	-0.33***	-0.25***	-0.28***	-0.26***
EU shocks	-0.21***	-0.17***	-0.25***	-0.22***	-0.21***
Diff	-0.07	-0.15*	0.00	-0.06	-0.05

This table reports the results for VIX put options. Panel A presents summary statistics of net demands, Panel B presents the difference in average net demands between high and low risk days, and Panel C presents the average value of market-maker (MM) demand shocks, end-user (EU) demand shocks, and their difference in days in the top 20% quintile of ΔVIX and top 20% quintile of VVIX.

Table A.2: Additional Evidence on Market-Maker Profit Maximization and the Variance Risk Premium Puzzle

Panel A. Option Returns and MM Volatility Exposure

	Average Option Return
MM Vol Exposure> 0	0.0283
MM Vol Exposure< 0	-0.0058*
Diff	0.0341.

Panel B. ΔVIXP on High vs. Low Risk Days

	Average ΔVIXP Difference
ΔVIX_H - ΔVIX_L	-0.66**
VVIX_H - VVIX_L	-0.17
VIX_H - VIX_L	-0.18
ΔSkew_L - ΔSkew_H	-0.43.
$r_{S\&P500,L}$ - $r_{S\&P500,H}$	-0.05

Panel A presents the average option returns on days when market makers have positive versus negative volatility exposure, along with the difference between these returns. Panel B presents the difference in average ΔVIXP (daily changes in the VIX premium) between high versus low risk days. High (low) risk days are defined as those in the top (bottom) quintile of ΔVIX, VVIX, VIX, or the bottom (top) quintile of ΔSkew and $r_{S\&P500}$. ***, **, *, and '.' indicate significance at the 0.1%, 1%, 5%, and 10% level, respectively.

Table A.3: Incorporating Alternative Observable Factors

MM vs. EU Demand Shocks on High-Risk Days

	Panel A. Extended VAR with ΔRV					**Panel B. Extended VAR with VVIX**					**Panel C. Extended VAR with ΔVVIX**				
Maturity	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***	***1***	***2***	***3***	***4***	***5***
			$\Delta\mathbf{VIX}_H$					$\Delta\mathbf{VIX}_H$					$\Delta\mathbf{VIX}_H$		
MM shocks	0.76***	0.70***	0.66***	0.61***	0.50***	0.69***	0.65***	0.56***	0.51***	0.39***	0.70***	0.65***	0.58***	0.51***	0.40***
EU shocks	0.63***	0.65***	0.58***	0.53***	0.48***	0.56***	0.59***	0.49***	0.42***	0.35***	0.56***	0.59***	0.50***	0.43***	0.37***
Diff	0.13*	0.05	0.07	0.08	0.02	0.13*	0.05	0.07	0.09	0.04	0.14*	0.06	0.08	0.08	0.04
			$\mathbf{VVIX}_H$					$\mathbf{VVIX}_H$					$\mathbf{VVIX}_H$		
MM shocks	0.30***	0.35***	0.31***	0.20***	0.17***	0.18***	0.20***	0.14**	0.10*	0.08	0.30***	0.33***	0.32***	0.20***	0.16**
EU shocks	0.23***	0.17***	0.18***	0.23***	0.24***	0.16***	0.14**	0.09*	0.07	0.09*	0.21***	0.17***	0.16***	0.23***	0.20***
Diff	0.07	0.17**	0.13*	-0.03	-0.07	0.02	0.07	0.05	0.02	-0.02	0.09	0.17**	0.15*	-0.03	-0.04

This table reports the average market-maker (MM) and end-user (EU) demand shocks, as well as their difference, during high-risk days, defined as those in the top quintile of either ΔVIX or VVIX. Results are presented for alternative VAR specifications. In Panel A, shocks are estimated using an extended VAR that includes ΔRV in addition to the baseline price and quantity variables. Panel B adds VVIX, while Panel C includes ΔVVIX. Statistical significance is denoted by ***, **, *, and '.' for the 0.1%, 1%, 5%, and 10% levels, respectively.