

Exchange-Traded Liquidity

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Abstract

We study the depth of the limit order book, dealer numbers, and market quality in exchange traded markets. We document an 80% reduction in the depth and in the number of participating dealers in the world's largest futures market, the S&P 500 E-mini contract, over the period from 2012 to 2022. We then propose a model of liquidity provision subject to participation and balance sheet costs in exchange-traded markets. In line with the model predictions, we show a negative relationship between dealer number and volatility, driven by balance sheet costs. We further show that the dealer number provides information about market fundamentals not contained in other classical liquidity measures.

Keywords: liquidity, volatility, dealers, leverage constraints, liquidity supply

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In recent years, waning liquidity in financial markets has been a highly topical discussion among practitioners and policymakers. Liquidity plays a pivotal role in financial markets, influencing the efficiency of asset trading, price discovery, and overall market stability. Bond market liquidity in particular have received attention. For example, Bao, O’Hara, and Zhou (2018) show that illiquidity in corporate bonds have increased following the Volcker rule, and O’Hara and Zhou (2021) examine the Covid-19-related corporate bond liquidity crisis, which caused the Federal Reserve to step in and act as a last resort market maker. More recently, liquidity concerns have spread to other asset classes, including equity markets. The IMF has warned that increased illiquidity can lead to decreased financial stability and the Financial Times reports that ‘Liquidity is terrible’.¹

In this paper, we document the state of liquidity in the world’s most traded derivative market, the S&P 500 E-mini futures contract.² We initially measure liquidity as the dollar volume of market depth, i.e., the number contracts offered as limit orders in the market multiplied by the contract prices. All limit orders are collected in the Limit Order Book (LOB) which shows how many contracts are available and at what prices. The depth of the LOB is a direct measure of liquidity: if many contracts are available to trade at the best bid and ask prices, incoming market orders will not move prices much. In addition to market depth, we can also measure the number of liquidity providers, i.e., the number of market participants that post limit orders, and we refer to them as the dealers.

We show that liquidity, measured by market depth in the LOB, has decreased by 80% between 2012 and 2022. Specifically, the average dollar volume available to trade at either the best bid price or best ask price was USD 18.4 million in 2012 and USD 3.6 million in 2022.³ This 80% drop in market depth is seen at all price levels of the LOB and at all times during the trading day. Importantly, we show that the decline in liquidity is directly attributed to a reduction in the number of liquidity providers, with the average number of dealers at the best bid and ask price falling from 52 in 2012 to 11 in 2022. The remaining dealers still provide market depth in the same quantities as prior to the liquidity dry-up, so individual dealers do not appear to have become more risk averse. Instead, 80% of dealers have stopped providing liquidity altogether, implying that high trading activity moves prices more compared to previously. This leaves the market exposed

¹See, www.imf.org and www.ft.com.

²The open interest (number of active contracts) of the E-mini is around 3 million. Assuming the index has a value of 5,000 and accounting for the index multiplier of USD 50, the total value of the market is USD 750 billion.

³All our results remain qualitatively the same, sometimes even stronger, if we define market depth as simply the number of contracts available in the LOB. We use dollar dollar volume instead of the number of of contracts to account for the increasing level of the S&P 500 index thought out sample period.

to further liquidity shocks as it now only require a few dealers leaving the market to greatly affect market functionality.

To study dealers’ optimal liquidity provision and its main determinants, we develop a simple theoretical framework. Our model is motivated by the observation that the lack of full participation in a market is at the heart of illiquidity, and when some liquidity providers withdraw due to frictions, others might not be able to take their place, having adverse effects on prices. Our model captures two important aspects of liquidity: the end users’ need to trade and dealers’ limited supply. The motivation for trading arises from hedging endowment or wealth shocks, which makes end users want to adjust their asset holdings. In turn, we posit that liquidity suppliers are subject to margin or leverage constraints and find it costly to participate in markets – see, e.g., Merton (1987) or Grossman and Miller (1988), among others. Margin constraints imply that dealers cannot provide liquidity to the extent they would do in frictionless markets, which lowers their expected profits. As a result, when the balance sheet constraints are tight and participation costs are high, dealers might completely withdraw from those markets, leading to adverse effects on price levels, liquidity, and volatility. We find that these constraints can lead to a negative relationship between price volatility and the equilibrium dealer numbers, as tighter constraints increase the former and decrease the latter. Further, an increase in the participation costs moves the dealer number-volatility relationship downwards—i.e., higher participation costs imply that in equilibrium a lower number of dealers will be present while keeping volatility constant. Finally, we show that if we allow margins to depend on volatility, as in Brunnermeier and Pedersen (2009), this further amplifies the negative relationship.

We obtain the LOB data from Refinitiv as tick data, containing every single change to the LOB timestamped to the millisecond. The data has only been recorded since 2009 and, to the best of our knowledge, it has not previously been used to measure liquidity in the academic literature. We can therefore provide a novel insight to the state of liquidity in one of the most important financial markets.

To test the model predictions, we start by demonstrating the negative relationship between liquidity and volatility. The dealer number and volatility demonstrate a strong negative correlation ($\rho = -0.41$ with a p -value of $8.97 \cdot 10^{-141} \approx 0$). Testing the contemporaneous liquidity-volatility relationship in a regression framework, we find that a 10 percentage point increase in volatility corresponds to 11 fewer dealers present in the market. This shows that dealer participation and volatility changes are closely related.

Importantly, we observe instances where liquidity (as expected) declines due to a spike in volatility, but afterwards, the market depth and number of dealers fail to return to their prior levels, even as volatility fully subsides. This suggests that volatility spikes can trigger permanent shocks to liquidity, with the most notable examples being February 5, 2018 (the VIX volmageddon event), and March 2020 (the Covid-19 market crash). To rationalize this in terms of the model, we consider margin and leverage constraints on the dealers. We find that some volatility shocks have led to lasting margin increases and that it is the margin increases that appears to cause the dealers to permanently exit the market. In turn, the permanent liquidity shock implies that the long-run relationship between the levels of liquidity and volatility has changed drastically over time. To test this, we show that margin costs independently explain liquidity when controlling for volatility. This leads us to the conclusion that it is the increased margin costs and costs of liquidity provision that are keeping liquidity low. Additionally, we also proxy for dealer wealth with the capital and leverage ratio of major banks, and show that these also explain the liquidity-volatility relationship.

Next, we show that the dealer number provides information that is not contained in traditional liquidity measures such as the bid/ask spread and price impact measures like Kyle (1985)'s λ . We show that traditional liquidity measures have low explanatory power against the dealer number, and that the dealer number remains significant in explaining volatility when controlling for the other liquidity measures.

Finally, we show that the dealer number explains returns. First, we show that there is a positive contemporaneous relationship between prices and dealers present in the market: when prices go down, fewer dealers are willing to offer liquidity by posting limit orders. This implies that the dealer number should help explain returns sensitive to liquidity. One such example is the overnight drift documented by Boyarchenko, Larsen, and Whelan (2023), which shows that there on average is a large positive price drift in the S&P 500 E-mini market during the overnight trading period. The overnight drift appears on nights following a large sell-off and price drop in the market around U.S. close, because liquidity is lower during the overnight period, and we therefore experience large positive price reversals. In this paper, we show that the overnight drift is strongest when the number of dealers also went down on the previous trading day: when the dealer number decreases, liquidity is even more limited during the night and the price reversals are correspondingly stronger.

Overall, we provide new insights into the state of liquidity in the S&P 500 E-mini contract and advocate the use of market depth and particularly the dealer number when describing liquidity. We

develop a model that explains liquidity through the number of market participants that are willing to provide liquidity and we show that this number is controlled by the participation cost. Empirically, we show that the dealer number is closely related to volatility and that it holds information not contained in traditional liquidity measures.

Literature: Numerous studies have explored the dynamics of liquidity and its implications. However, standard market microstructure models typically assume that market makers are always present to provide liquidity. These models typically find that liquidity and price volatility are positively correlated; see, e.g., Kyle (1985) and Glosten and Milgrom (1985), who show that asymmetric information decreases liquidity measured by Kyle’s λ (price impact) and by the bid-ask spread, and price volatility.

Our analysis of participation decisions and equilibrium prices is closely related to those in Grossman and Miller (1988), Huang and Wang (2009, 2010), and the analysis on participation costs of Vayanos and Wang (2012, 2013). In fact, Grossman and Miller (1988) find that higher participation costs lead to lower dealer numbers and higher volatility, thus obtaining a negative relationship between dealer participation and volatility. Via this channel Vayanos and Wang (2012, 2013) highlight that an increase in the participation cost lowers the number of liquidity providers and raises illiquidity measured by Kyle’s λ and price reversal, measured by (the negative of) return autocorrelation. Vayanos and Wang (2012, 2013) do not analyse the impact of participation costs on volatility, but, as we show in the Internet Appendix, in their model higher participation costs also lead to higher volatility. However, in the absence of good proxies for participation costs and only relying on anecdotal evidence, it is hard to take these models to the data. In contrast, our model highlights the role of balance sheet space to explain the negative relationship between dealer number and volatility.

The paper is also related to the literature examining the effects of the margin regulation on stock market volatility and other market variables. The early literature, starting with Moore (1966) and Officer (1973), concluded that margin regulation has no major impact on market volatility (see also Ferris and Chance (1988), Kupiec (1989), Schwert (1989), and Hsieh and Miller (1990), and Kupiec (1997) for an extensive review). In contrast, we show that higher margins lead to a lower dealer number and market depth, and higher volatility. The paper is also related to Frazzini and Pedersen (2014), who use the TED spread as a proxy for the constraint of investors, and Jylhä (2018), who uses the minimum initial margin requirement to find robust empirical evidence that tighter

leverage constraints result in a flatter security market line, but they do not study volatility or liquidity.

Several recent studies have highlighted new channels to better measure liquidity. Hendershott, Li, Livdan, and Schürhoff (2024) show that total cost of immediacy is significantly higher than observed costs. Duffie, Fleming, Keane, Nelson, Shachar, and Van Tassel (2023) argue that when dealer balance sheet utilization is sufficiently high, liquidity is greatly affected.

The rest of the paper is organized as follows. Section I briefly discusses the setup of electronic exchanges and limit order books to motivate that market depth and the number of active dealers is essential when measuring liquidity. Section II presents a theoretical framework for dealer participation and derives testable predictions for liquidity. Section III first documents the historic liquidity of the S&P 500 E-mini contract. Next, the model predictions are tested. It is confirmed that there is a negative liquidity-volatility relationship and that increased dealer participation costs (measured with margin cost) lowers liquidity relative to volatility. Finally, we compare the number of dealers to classical liquidity measures and show that the dealer number remains significant when explaining volatility while accounting for the other liquidity measures. E tests how well the dealer number explain asset price returns sensitive to liquidity shocks. Section IV concludes.

I. Central Exchanges and Futures Contracts

In this section, we briefly describe the setup of central exchanges to motivate the variables and mechanics in our model. Like forwards, a futures contract specifies the exchange of an asset for a specified price at a specified future date. Unlike forwards, futures are standardized contracts that trade on exchanges, making them more liquid due to larger trading volume of each specific contract. Futures are also margined, making them significantly less exposed to credit risk. The first S&P 500 futures contract was introduced in 1982 and quickly became popular as it allowed traders to easily speculate on or hedge the equity market. The e-mini futures started trading in 1997 and became the most traded equity contract by 2004.

Futures contracts trade on central exchanges, where market participants post either limit orders or market orders. A limit order is an order to buy or sell at a specific price – the bid and ask price, respectively. Limit orders supply liquidity to the market and are registered in the limit order book (LOB). In contrast, a market order is instantly executed at the best available price in the LOB and therefore consume liquidity. The best bid and ask prices are referred to as level 1 in the LOB and

the second best bid and ask prices are referred to as level 2 in the LOB, etc. Market participants posting limit orders are referred to as dealers. If a dealer posts limit orders at both the best bid and best ask price, and these orders are executed, she will earn the bid–ask spread. This type of market making is performed by a limited number of high frequency traders that act as de facto market makers.

If a large number of dealers are providing liquidity by posting limit orders, the bid–ask spread will be low due to market competition, making the spread a natural measure of liquidity. However, the spread does not function well as a liquidity measure in large and competitive futures markets, because the spread historically has been constant and equal to its effective minimum which is the minimum possible price change in the market. Therefore, we propose to measure liquidity with the market depth or *dollar volume*, which is defined as the number of contracts available in the LOB $\times$ the price of the contract. Effectively, market depth is an inverse measure of price impact: a high market depth implies that prices move only a little even when trading volume is high.

The dollar volume for a given level of the LOB is computed as

$$DVol_j = C_j \cdot P_j \cdot m, \quad (1)$$

where $j = 1, \dots, 5$ is the order book level, C_j is the number of contracts available (i.e., the number of posted limit orders), P_j is the price level, and m is the index multiplier. Since we know the total number of dealers, we can rewrite equation (1) as

$$DVol_j = N_j \cdot \frac{C_j}{N_j} \cdot P_j \cdot m, \quad (2)$$

where N_j is the number of dealers that are posting a limit order and C_j/N_j is the average number of contracts offered per dealer. We perform this extension of equation (1) to test whether it is the total number of dealers that drive liquidity.

II. Theoretical framework

To study dealers' optimal liquidity provision and its main determinants, we develop a simple theoretical framework. Our model is motivated by the observation that the lack of full participation in a market is at the heart of illiquidity, and when some liquidity providers withdraw due to frictions,

others might not be able to take their place, having adverse effects on prices. Due to the endogenous participation decision, equilibrium dealer number becomes a valid measure of market liquidity (unlike in traditional models in which all market makers are always present), and we explore its relationship with return moments to derive testable predictions.

A. *Setting*

There are three dates, $t = 0, 1$, and 2 . The financial market consists of a riskless and a risky asset that can be traded at date 1 and pay off at date 2. The riskless asset is in elastic supply and its riskfree net return is normalized to zero. The risky asset, whose supply is normalized to zero for simplicity, pays off D units, where D has mean $\bar{D}$ and variance σ^2 . Using the riskless asset as the numeraire, we denote by p the risky asset's price at date 1.

The economy is populated by two types of agents, end users and dealers. End users, in exogenously given mass n , have exponential utility with the coefficient of absolute risk aversion α . For convenience, we express their utility as certainty-equivalent wealth, i.e., as

$$-\frac{1}{\alpha} \log \mathbb{E} [\exp \{-\alpha W_2^e\}], \quad (3)$$

where W_2^e is the terminal (date-2) wealth. In turn, their terminal wealth consists of the starting wealth W^e , capital gains from trading the risky asset, and an endowment $z(D - \bar{D})$ of the consumption good at date 2 that covaries with the payoff of the risky asset. Formally,

$$W_2^e = W^e + x_1^e (D - p) + z (D - \bar{D}), \quad (4)$$

where x_1^e denotes their position in the risky asset. We assume that the variable z is Gaussian with mean zero and variance σ_z^2 , and is independent of D . While the endowment is received at date 2, agents learn z at date 1. Since the endowment is correlated with D , it generates a hedging demand. When, for example, $z > 0$, the endowment exposes agents to the risk that D will be low, and agents hedge against that risk by selling the risky asset. We assume that the endowment is perfectly correlated with D for simplicity; what matters for our analysis is that the correlation is non-zero and hence generates trade.

Dealers are assumed to be risk neutral and do not receive any endowment shocks, but are subject

to a constraint on the position they can take. Formally, they maximize their expected date-2 wealth,

$$\mathbb{E} [W_2^d], \quad (5)$$

subject to the budget constraint

$$W_2^d = W^d + x_1^d (D - p) \quad (6)$$

and the margin constraint

$$\kappa |x_1^d| \leq W^d, \quad (7)$$

where W^d denotes their starting wealth, x_1^d is their position in the risky asset, and $\kappa \geq 0$ is the capital requirement associated with trading the risky asset. The margin constraint (7) states that in order to undertake a trade of size $|x_1^d|$ dealers must commit $\kappa |x_1^d|$ of their scarce capital. Historically, margins have been set between 5% and 10% of the E-mini's contract value.

To simplify the notation, we define $w_\kappa^d \equiv W^d / \kappa$ as the balance sheet space dealers can allocate to the risky asset, where we indicate the dependence on the margin κ for further reference. This implies that (7) is equivalent to

$$|x_1^d| \leq w_\kappa^d, \quad (8)$$

In equilibrium, end users initiate trades with dealers to share risk. Because they can be thought of as consuming market liquidity, we also refer to them as liquidity demanders. Moreover, we refer to z as the liquidity shock. Dealers, who are risk neutral and have no endowment shocks accommodate the trades of liquidity demanders, supplying liquidity. Thus, we also refer to them as liquidity suppliers.

In a frictionless economy, all agents would be present in all markets periods. Thus, any seller of an asset, for example, can have immediate access to the entire population of buyers. In practice, however, agents face costs of market participation. Such costs include buying trading infrastructure or membership of a financial exchange, having capital available on short notice, monitoring market movements, etc. To obtain a limited liquidity supply, we assume costly participation of dealers in the form of incurring a cost c to enter the market and trade at date 1. Consistent with the notion that participation is an ex-ante decision, we assume that agents must decide whether or not to incur c at date 0, i.e., before observing the price at date 1.⁴ We denote the mass of available dealers by

⁴If the decision can be made contingent on the price at date 1, then c is a fixed transaction cost rather than a participation cost. We consider transaction costs as an alternative in the appendix.

$N_{max} \in (0, \infty]$, also allowing for an infinite pool of them, and by N the mass of dealers actually participating in the market and providing liquidity at date 1.

B. Equilibrium

In this section we first solve for the equilibrium of the model. We go backwards from date 1 to date 0. We first compute the equilibrium price and quantities at date 1 given the mass of market participants, and then we study the entry decision of dealers at date 0.

At date 1, end-users choose holding x_1^e of the risky asset to maximize the expectation of (3). Substituting (4) into (3), after some algebra we obtain that the optimization problem of end-users is equivalent to

$$\max_{x_1^e} W^e + x_1^e (\bar{D} - p) - \frac{1}{2} \alpha \sigma^2 (x_1^e + z)^2. \quad (9)$$

From here, optimal demand of liquidity demanders is given by

$$x_1^e = \frac{\bar{D} - p}{\alpha \sigma^2} - z. \quad (10)$$

It has two components: a downward-sloping demand curve, according to which they buy the asset as long as the price is below the fundamental value and (short) sell otherwise, and a term influenced by the liquidity shock z . When, for example, z is positive and large, liquidity demanders are willing to sell because their endowment is positively correlated with the asset.

A liquidity supplier chooses holdings x_1^d of the risky asset to maximize (5). Substituting in (6) and taking the constraint (7) into account, after some algebra we obtain

$$x_1^d = \begin{cases} -w_\kappa^d & \text{if } p > \bar{D} \\ \in [-w_\kappa^d, w_\kappa^d] & \text{if } p = \bar{D} \\ w_\kappa^d & \text{if } p < \bar{D}. \end{cases} \quad (11)$$

Dealers as liquidity suppliers are willing to buy the risky asset as long as it trades below its expected payoff $\bar{D}$ and are willing to sell otherwise. Since they are risk neutral, they trade up to the maximum amount allowed by their leverage constraints.

Market clearing requires that aggregate demand equals supply, i.e.,

$$N \cdot \text{sgn}(\bar{D} - p) w_\kappa^d + n \cdot \left(\frac{\bar{D} - p}{\alpha \sigma^2} - z \right) = 0$$

which implies

$$p = \begin{cases} \bar{D} - \alpha\sigma^2 \left(z + \frac{N}{n}w_\kappa^d \right) & \text{if } z < -\frac{N}{n}w_\kappa^d \\ \bar{D} & \text{if } |z| \leq \frac{N}{n}w_\kappa^d \\ \bar{D} - \alpha\sigma^2 \left(z - \frac{N}{n}w_\kappa^d \right) & \text{if } z > \frac{N}{n}w_\kappa^d. \end{cases} \quad (12)$$

Naturally, the finite mass of dealers and their position limits implies that they can fully absorb the liquidity shock z as long as the shock is small. In this case, dealers drive the market price back to its expectation, $\bar{D}$. In contrast, when the liquidity shock is large, end users can only partially share risk with dealers and require a premium for bearing risk.

Next we consider dealers' liquidity supply decision. Due to the risk neutrality assumption, their aggregate position is either $\frac{N}{n}w_\kappa^d$ or $-\frac{N}{n}w_\kappa^d$, and, as long as they decide to enter the market, their expected interim utility (after the liquidity shock realization but before the asset payoff) is

$$\mathcal{U}_1^d(z) = \begin{cases} W^d - c - w_\kappa^d \alpha \sigma^2 \left(z + \frac{N}{n}w_\kappa^d \right) & \text{if } z < -\frac{N}{n}w_\kappa^d \\ W^d - c & \text{if } |z| \leq \frac{N}{n}w_\kappa^d \\ W^d - c + w_\kappa^d \alpha \sigma^2 \left(z - \frac{N}{n}w_\kappa^d \right) & \text{if } z > \frac{N}{n}w_\kappa^d, \end{cases} \quad (13)$$

which consist of the starting wealth, the participation cost c , and the trading gain calculated from (11) and (12). After some algebra, we obtain that the ex ante expected utility of dealers who enter the market is

$$\mathcal{U}_0^d = W^d - c + 2\alpha\sigma^2\sigma_z w_\kappa^d \Psi \left(-\frac{1}{\sigma_z} \frac{N}{n} w_\kappa^d \right), \quad (14)$$

where

$$\Psi(x) \equiv \phi(x) + x\Phi(x) \quad (15)$$

is a strictly increasing convex function, and ϕ and Φ denote the pdf and cdf of the standard normal distribution.

Equations (13) and (14) highlight the two effects higher dealer balance sheet space has on realized and expected profits. Higher wealth or lower margins allow risk neutral dealers to take larger positions, which in turn bring the price closer to the expected asset payoff and lowers the realized and expected dollar return. As a result, the expected profit is a hump-shaped function of w_κ^d . Using (14), we can show that higher balance sheet space allows for higher expected profits as long as

$$0 \leq w_\kappa^d \leq \bar{w}_\kappa^d \equiv \frac{n}{N} \sigma_z \bar{w} \quad (16)$$

and $\bar{w} > 0$ the only root of $0 = \phi(-\bar{w}) + 2(-\bar{w})\Phi(-\bar{w})$. From now on we make the assumption that we are in this intuitive range.

Dealers enter the market as long as their expected utility is at least as high as the utility from staying out:

$$\mathcal{U}_0^d \geq \bar{\mathcal{U}}_0^d \equiv W^d, \quad (17)$$

Since we require $N \geq 0$, (14) and (17) imply the following result:

Proposition 1. *Let $\bar{c}(w_\kappa^d) \equiv \sqrt{2/\pi} \alpha \sigma^2 \sigma_z w_\kappa^d$. If $c \geq \bar{c}(w_\kappa^d)$, we have $N = 0$. If $0 < c < \bar{c}(w_\kappa^d)$, dealers enter the market as long as their equilibrium mass reaches*

$$N = -n\sigma_z \frac{1}{w_\kappa^d} \Psi^{-1} \left(\frac{c}{2\alpha\sigma^2\sigma_z} \frac{1}{w_\kappa^d} \right) > 0. \quad (18)$$

If (16) also holds, the equilibrium dealer number N is increasing in dealers' wealth and decreasing in the margin, $dN/dw_\kappa^d > 0$.

Proposition 1 states that if the entry cost is too high compared to dealers' available balance sheet space $w_\kappa^d \equiv W^d/\kappa$, they will stay out of the market, but if the entry cost is moderate, we obtain a finite number of dealers deciding to provide liquidity in equilibrium. In turn, the equilibrium number of dealers is increasing in dealer balance sheet space.

Combining Proposition 1 with (12) allows us to express the equilibrium price volatility at date 1 in terms of model primitives:

Proposition 2. *When $c \geq \bar{c}(w_\kappa^d)$, price volatility is $\text{Var}[p] = (\alpha\sigma^2)^2 \sigma_z^2$. When $0 < c < \bar{c}(w_\kappa^d)$,*

$$\text{Var}[p] = 2(\alpha\sigma^2)^2 \sigma_z^2 \Gamma \left(\Psi^{-1} \left(\frac{c}{2\alpha\sigma^2\sigma_z} \frac{1}{w_\kappa^d} \right) \right). \quad (19)$$

where $\Gamma(x) \equiv \Phi(x) + x \cdot \Psi(x)$ is a strictly increasing function. As a result, $d\text{Var}[p]/dw_\kappa^d < 0$.

Combining Propositions 1 and 2, we obtain the following result regarding the relationship of price volatility and equilibrium dealer number as a result of time-variation in w_κ^d while keeping other model parameters constant

Corollary 1. *Assume that $0 < c < \bar{c}(w_\kappa^d)$. Then we have*

$$\frac{dN}{dw_\kappa^d} > 0 \text{ and } \frac{d\text{Var}[p]}{dw_\kappa^d} < 0.$$

Suppose we allow w_κ^d to be time varying while keeping other model parameters constant. As a result, Corollary 1 implies a negative relationship between return volatility and the equilibrium number of liquidity providers, and the mechanism is through the impact of margin constraints dealers are subject to: more balance sheet space (lower dealer wealth and/or higher margins) lead to a lower number of liquidity providers and higher volatility.

Next, we examine how the relationship between volatility, the number of liquidity providers, and available balance sheet capital changes if the participation cost increases:

Proposition 3. *Assume that $0 < c < \bar{c}(w_\kappa^d)$ so that $N > 0$. An increase in c while keeping c/w_κ^d constant lowers N but does not affect $\text{Var}[p]$.*

A straightforward implication of Proposition 3 is the following:

Corollary 2. *When participation gets more costly and c increases, the $N - \text{Var}[p]$ curve shifts “downwards”: the same level of $\text{Var}[p]$ corresponds to a lower equilibrium dealer number N .*

Finally, consider the case when volatility has an impact on the dealers’ balance sheet space. There could be at least two reasons for this relationship. First, margins are typically determined endogenously as in, e.g., Brunnermeier and Pedersen (2009). In fact, there is evidence that CME increase their margins after periods of high volatility.⁵ Second, volatility typically spikes in down markets, therefore, volatility rises when dealers suffer losses. In both cases, volatility increases and the margin constraint gets tighter in the form of w_κ^d decreasing. We show that this feedback effect further amplifies the negative relationship between volatility and liquidity supply:

Proposition 4. *Suppose margins are set as an increasing function of price volatility. A decrease in balance sheet space then XXX*

Our model also yields testable predictions regarding the relationship between returns and dealer numbers. First, let us assume that at date 0 the price is the unconditional expectation of the asset, $\bar{D}$ – this would also be in line with the assumption that dealers are risk neutral and, absent any constraints, any infinitesimal measure of them would drive the price back to $\bar{D}$.

From (12), realized returns between dates -1 and 0 are given by $R_1 = p - \bar{D}$ and expected returns between dates 1 and 2, conditional on the liquidity shock, are $E[R_2|z] = E[R_2|p] = \bar{D} - p$. Since dealers are assumed to be risk neutral and they are subject to the balance sheet constraint

⁵See, e.g., <https://www.cmegroup.com/education/articles-and-reports/understanding-margin-changes.html>.

(8), it is imminent that the expected dollar return must compensate them for paying the cost of liquidity provision, c , and ex ante expected returns are $E[R_2] = -E[R_1] = c \frac{1}{w_\kappa^d}$. Together with Proposition 1, these imply the following result:

Corollary 3. *There is a positive relationship between dealer numbers and contemporaneous returns, and a negative relationship between dealer numbers and expected future returns: $dE[R_2]/dw_\kappa^d > 0$ and $dE[R_1]/dw_\kappa^d < 0$.*

C. Testable Predictions

We summarize the testable predictions from the theoretical framework:

Corollary 1 implies the following predictions:

Prediction 1. *Lower dealer wealth and higher margins lead to higher volatility.*

Prediction 2. *Lower dealer wealth and higher margins lead to a lower number of liquidity providers.*

Prediction 3. *There is a negative relationship between return volatility and the number of liquidity providers.*

Corollary 2 implies the following predictions:

Prediction 4. *When participation gets more costly, an increase in c moves the $N - \text{Var}[p]$ curve downwards.*

Suppose now that higher price volatility leads to tighter margins. Our model suggests that the resulting feedback effect further amplifies the negative relationship between volatility and liquidity supply. Assuming that new capital then enters the market slowly (Duffie, 2010), we would expect the following implication to hold:

Prediction 5. *After a period of high volatility, the equilibrium dealer number drops and recovers slowly.*

Prediction 6. *There is a positive relationship between dealer numbers and contemporaneous returns, and a negative relationship between dealer numbers and expected future returns.*

D. Discussion

Before we turn our attention to the empirical analysis, we discuss our assumptions and the robustness of the results, and relate our findings to those in the previous literature.

The solution of our model and hence its testable implications hinge on a couple of assumptions. In the model presented above, participation costs paid by potential liquidity suppliers ensures that we obtain an endogenously determined number of dealers as opposed to this number being exogenously given. If we set $c = 0$, the whole pool of potential risk neutral dealers would enter the market because, as (14) shows, they would have positive expected profits from those states of the world in which the realization of the liquidity shock is sufficiently large. If $N_{\max}$ is finite, the above argument implies that volatility decreases in $N_{\max}$ and in w_{κ}^d , in line with Prediction 1. Further, lower balance sheet space w_{κ}^d increases volatility, in line with Prediction 2. However, since $N_{\max}$ is exogenously given, it is unrelated to w_{κ}^d , in contrast with Prediction 3. Having $c > 0$ participation cost thus (i) provides us an equilibrium relationship between N and $\text{Var}[p]$, and the mechanism behind this relationship is via the impact of balance sheet space w_{κ}^d on these two variables; and (ii) leads to Predictions 3 and 4.

Suppose now instead dealers are not subject to margin constraints. Since they are risk neutral, any positive mass of them would compete any potential profits away by driving the price to $\bar{D}$. But as long as entry is costly, $c > 0$, the only equilibrium is then the one with dealers staying out of the market, $N = 0$. Therefore, none of our four predictions would be relevant in this case.

The assumption that dealers are risk neutral has no qualitative impact on our results. In the Internet Appendix we present a version of the model that allows for risk aversion. Its main implication is that dealers' leverage constraints only occasionally bind, depending on the size of the liquidity shock, which further complicates the expressions for the equilibrium price, quantities and moments, without providing additional insights about their dynamics.

Our analysis of participation decisions and equilibrium prices is closely related to those in Grossman and Miller (1988), Huang and Wang (2009, 2010), and Vayanos and Wang (2012, 2013). In fact, Grossman and Miller (1988) find that higher participation costs lead to lower dealer numbers and higher volatility, thus obtaining a negative relationship between dealer participation and volatility. Via this channel Vayanos and Wang (2012, 2013) highlight that an increase in the participation cost lowers N and raises illiquidity measured by Kyle's lambda and price reversal, measured by (the negative of) return autocorrelation. Vayanos and Wang (2012, 2013) do not analyse the impact of

participation costs on volatility, but, as we show in the Internet Appendix, in their model higher participation costs also lead to higher volatility. However, in the absence of good proxies for participation costs and only relying on anecdotal evidence, it is hard to take these models to the data. In contrast, our model highlights the role of balance sheet space to explain the negative relationship between N and volatility.

III. Evidence

In this section we first describe the state of liquidity for the E-mini contract. Then, we test our model predictions by first exploring the empirical relationship between liquidity and volatility, and next considering participation costs and their effect on the dealer number and volatility. Our empirical analysis focuses is on the S&P 500 E-mini futures contract because it is the most traded equity contract and S&P 500 index is a good proxy for the U.S. market portfolio.

A. Data

Our primary data source is the market depth of futures contracts traded on CME Globex, an electronic exchange where market participants can submit limit orders and market orders. The data are obtained from Refinitiv Data (previously Thomson Reuters) and, for level 1 to 5 of the LOB, contain (i) the number of contracts (limit orders) available, C , (ii) the number of dealers (market participants that are posting limit orders), N , and (iii) the quoted price, P . The E-mini depth data is available from January, 2009 and we end our sample period in December 2022.

The raw data come as tick data, meaning that every single update to the limit order book is registered as a new observation. We choose to sample the tick data, which contain millions of observations per day, both at a daily frequency and at a 5-minute frequency, giving us 288 observation per trading day. This allows us to also study the intraday behaviour of liquidity in high frequency. For each 5-minute interval, C , N and P are computed as averages of all observations in a given interval.

We note, that the data do not show the number of contracts offered by individual dealers, so we cannot identify individual dealers or how dealers change their positions. For example, if there is 10 available contracts to buy from three dealers at an ask price of 100 at level 1 of the LOB, then we know that the three dealers are posting at least one contract each, but we do not know if they offer 1,1, and 8 contracts, respectively, or 3, 3 and 4 contracts.

In accordance with our model, we measure liquidity as the number of dealers present in the market, however, all results hold equally well when measuring liquidity with the available market depth (dollar volume) because it effectively is the number of dealers that controls the market depth. We measure volatility using daily realized volatility, RV , computed from logarithmic returns sampled at a 5-minute frequency throughout the trading day.⁶

B. Liquidity in the S&P 500 E-mini Futures Market

We start by documenting how liquidity of the E-mini contract has evolved. Figure 1 plots the time series of liquidity measured by market depth (dollar volume). The daily dollar volume is computed as the average of all 5-minute observations during the trading day. Overall, depth is highly time-varying and exhibits downwards jumps that are followed by prolonged periods where the depth slowly rebounds.⁷ Notable examples of jumps are the financial crisis (the September, 16, 2008 event is not included in our sample period, but the rebound in depth is evident), the 2010 flash crash, the 2011 European sovereign debt crisis, the 2015–2016 stock market selloff, the February 5 2018 VIX spike (volmageddon) and the 2020 COVID-19 stock market crash. Surprisingly, the two latter shocks appear to have had permanent effects as depth has not rebounded to its previous levels.

As described in equation (2), market depth can be decomposed into the number of dealers and the depth offered per dealer. This allows us to test what drives changes in market depth: does the number of dealers, N , change, or do each individual dealer change the number of contracts that they are willing to trade. Figure 2 (a) displays the time series of active dealers and shows that there is indeed fewer dealers posting limit orders over time. Figure 2 (b) plots the time series of depth offered per dealer. While the dollar volume offered per dealer is time-varying and drops during crises, we do not observe a downward trend as we do for the dealer number. In a simple linear regression of the daily time series, the dealer number explains 79% of variation in market depth, while depth per dealer explains 41%.⁸ Therefore, the long-term lower depth level observed in figure 1 is primarily driven by a lower number of dealers. This empirically supports our emphasis on using the participation decision of dealers as a liquidity measure.

Considering the overall trend in market depth, the average dollar volume available to trade at

⁶All following results on volatility hold equally well when using the VIX as the measure of volatility.

⁷This holds for all individual levels of the LOB and for both the number of contracts available and the dollar volume available).

⁸In a multiple linear regression, the dealer number and depth per dealer explains 96% of variation in total depth.

both the best bid price and best ask price was USD 18.4 million in 2012 and USD 3.6 million in 2022. This corresponds to a drop of 80% and similar drops are seen at all price levels of the LOB and at all times during the trading day. The decline in depth is perfectly in line with change in dealer numbers, where there in 2012 was an average of 52 dealers per day at level 1 of the LOB, and 11 in 2022. Likewise, the average dealer number across level 1 to 5 was 100 in 2012 and 21 in 2022 – again a drop of 80%.

[Insert Figure 1 and 2 here]

Using CFTC data, we can compare the number of active dealers, N , (i.e. the number of market participants that are posting limit orders) to the number of registered CFTC dealers in the market. Market participants that are registered as dealers at CFTC mainly consists of large U.S. and non U.S. banks. We describe the CFTC trader types in more detail in the Internet Appendix. Figure 3 plots the time series of N versus the CFTC dealer number. In some periods, N is higher than the number of registered dealers, implying that other trader types must be posting limit orders. At other times, particularly during and following market slumps, N is lower than the number of CFTC dealers, meaning that some CFTC dealers choose not to provide liquidity. This has consistently been the case since 2018, and it confirms that dealers actively decide when to provide liquidity and when to step out of the market.

[Insert Figure 3 here]

Our data also allow is to study the intraday behavior of dealers. A trading day on CME Globex, where the E-mini exclusively trades, starts at 18:00 eastern time (ET) and ends the next day at 17:00 ET. There is a maintenance break from 16:15 to 16:30 ET. Figure 4 displays the average intraday pattern of liquidity measured by (a) the market depth (dollar volume available to trade) and by (b) the number of dealers for level 1 to 5 of the LOB. The dollar volume and dealer number at a specific time in the plots are computed as an average of the given 5-minute interval across all trading days in our sample. The intraday pattern of market depth closely resembles the pattern of trading volume (see, e.g., Boyarchenko, Larsen, and Whelan (2023), Figure 8), where liquidity is lowest during Asian trading hours and highest during U.S. trading hours. There is a spike in liquidity at U.S. close which is when most managers adjust their portfolios. The number of dealers does not increase at close, suggesting that each individual dealer supply more liquidity. The pattern

of market depth suggests that liquidity generally is provided when it is needed, i.e., when trading volume is high, and this is in line with classical market microstructure models. The plot is *not* cumulative, meaning that, e.g., the level 3 depth is equal to only the depth at level 3 and not level 1 to 3. On average, there are more dealers and a higher dollar volume at level 2 to 5 of the order book compared to level 1.

Considering the recent decrease in volatility and the intraday pattern, we find the the drop in liquidity has been almost uniform across the trading day. This is seen in Figure A.1 which plots the intraday pattern of liquidity as in Figure 4, but for the subsamples 2010 to 2014 and 2020 to 2022. There where on average 32 dealers during Asian trading hours in 2010 to 2014 and 9 dealers in 2020 to 2022. During U.S. trading hours, there where 133 in 2010 to 2014 and 24 in 2020 to 2022.

[Insert Figure 4 here]

C. *The Dealer–Volatility Relationship*

We now move to the predictions of our model. Prediction 1 states that there is a negative relationship between return volatility and the number of dealers. This is explored in figure 3, which displays the time series of the daily average number of active dealers, N , in the E-mini market along with the daily realized volatility. The figure confirms that the dealer number and volatility exhibits a strong negative correlation. Specifically, the correlation is $\rho = -0.41$ with a p -value of $8.97 \cdot 10^{-141} \approx 0$. In Figure 5, we further explore the liquidity–volatility relationship by plotting the average daily number of dealers, N , against daily realized volatility. We see that the N -to-volatility ratio peaked during 2009 to 2013 and has been at its lowest from 2018 and onwards. Figure 5 also shows that the liquidity–volatility relationship is non-linear. This is highlighted by the quadratic regressions in the figure, where the dealer number is regressed on realized volatility. The regressions have R^2 values around 0.7 and t -statistics exceeding 10. To investigate the time fixed effects in more detail, we disaggregate observations into years in Figure 6. We find that the negative relationship between volatility and liquidity persists across all sample years, but liquidity relative to volatility shows a significant decrease in recent years. Our initial empirical investigations therefore lead to two key conclusions:

1. Volatility significantly influences the liquidity provided by market makers, displaying a negative relationship.

2. In comparison to previous years, the current level of liquidity relative to volatility has notably decreased.

[Insert Figures 5 and 6 here]

We now proceed with a formal analysis of the contemporaneous interplay between liquidity and volatility. Figure 3 implies that this relationship has changed over time in terms of levels.⁹ Figure 3 further shows that liquidity and volatility cannot be cointegrated due to the persistent downward jumps in liquidity, and we therefore need to model the relationship in terms of differences.

Let $\Delta N_t \equiv N_t - N_{t-1}$ be the daily change in number of dealers, and let $\Delta \sigma_t \equiv \sigma_t - \sigma_{t-1}$ denote the daily change in price volatility in percentages. We assume that

$$\Delta N_t = f(\Delta \sigma_t) + \epsilon_t. \quad (20)$$

Regression (i), (ii) and (iii) in table I displays coefficients for 3 specifications of $f(\cdot)$ in the above regression. We utilize both volatility and variance (i.e., squared volatility) as explanatory variables, as suggested by the non-linear relationship observed in Figure 5. Across all regressions, a strong and negative relationship emerges between liquidity and volatility, with all β -coefficients in the simple linear regressions being negative and statistically significant at standard levels. Using both volatility and variance as explanatory variables, the two remain statistically significant with the coefficient of variance being positive. This aligns with the convex relationship evident in Figure 5. Employing the third specification in Table I, we find that a 10 percentage point increase in volatility leads to a decrease in dealer number by $-1.19 \cdot 10 + 0.93 \cdot 1 = -10.97 \approx -11$. Table A.1 in the Internet Appendix provides bootstrapped confidence intervals for the β -estimates and shows that zero is not contained in any of the intervals. Table A.2 shows that accounting for possible time fixed effects do not affect the regression results, indicating that when modelled in differences, dealers' response to volatility changes have remained numerically the same across the sample period. Here, we note that time fixed effect will have significant explanatory power when the regression is performed in levels due to the non-stationarity of the dealers number as see in figure 3.

[Insert Table I here]

⁹This is also demonstrated in Figure A.4 in the Internet Appendix, which shows the residuals of a regression in levels of dealer number on volatility. The residuals violates the assumption of weak exogeneity, i.e., that $E[\epsilon_t | \sigma_t] = 0$.

D. Participation Costs

In this section, we test how participation costs affect liquidity and volatility. Our model implies that lower dealer wealth and higher margins imply higher volatility (Prediction 2) and lower liquidity (Prediction 3). Additionally, Prediction 4 states that higher participation costs move the dealer-volatility curve downwards and Prediction 5 states that the dealer number will be slow to recover following a period of high volatility. Higher participation costs can therefore explain why the dealer number have dropped in recent years even though volatility is low. We cannot measure the dealer wealth directly, but margins are observable at all times. The futures margin requirement is the amount of cash that a market participant must deposit and keep on hand with her broker when holding a futures position. Futures margins are typically at 3-12% of the notional value of the contract, and they generally go up when price volatility increases, but the exact margin size is proprietary to the CME.¹⁰ Figure 7 depicts the time series of margins both in U.S. dollars and in percent of the E-mini contract value. We observe a jump in margins close to 100% during the COVID-19 stock market crash where volatility also was at extreme levels. This is in line with standard clearing house policy of adjusting margins relative to risk as measured through volatility, and testing for this, we find that volatility explains next day's margins (see Table A.3). What is surprising, is that margins have remained at elevated levels since 2020 and this could potentially explain the permanent decrease in market depth, but this is in line with Abruzzo and Park (2016)) who also find that the CME is quick to increase margins in response to volatility shocks but slow to decrease them.

Regression (iv) and (v) in table I confirms that the margin percent explains liquidity measured as the number of dealers – also when controlling for volatility, and, indeed, we see that higher margins reduces the number of dealers. Specifically, a margin increase of 1 percentage point causes the expected number of dealers to drop by 14 all else equal. Additionally, regression (ii) in table III affirms the predicted positive relationship between margins and volatility. Since margins have remained elevated since 2020, they remain as a natural candidate for explaining the E-mini depth dry-up. However, we note that according to the model, other potential increases to dealers' costs can also explain the low number of dealers and depth.

[Insert Figure 7 here]

¹⁰See www.cmegroup.com/education/courses/introduction-to-futures/margin-know-what-is-needed.html

Now, we try to proxy the dealer wealth using the capital ratio of dealers as proposed by He, Kelly, and Manela (2017). Recall the model prediction that lower dealer wealth leads to lower liquidity and higher volatility. Thus, a higher capital ratio should increase the dealer number and decrease volatility. We do not know the identities of E-mini futures dealers, but the CFTC states that registered dealers consist of large U.S. and non-U.S. banks. These banks are active as dealers in most large markets and we therefore use the He, Kelly, and Manela (2017) capital ratio as a proxy for the capital ratio of E-mini dealers. The He, Kelly, and Manela (2017) capital ratio is available at a daily frequency and is based on the list of NY Fed primary dealers.

Table II confirms that the capital ratio and the dealer number are negatively correlated. While the capital ratio has low explanatory power in itself, there is a strong interaction effect through the volatility. Table III shows that a higher capital ratio leads to lower volatility. The tables also include the daily signed trading volume of the E-mini contract. We use the signed volume as a proxy for the dealer balance sheet utilization rate, which, as argued by Duffie, Fleming, Keane, Nelson, Shachar, and Van Tassel (2023), negatively affects liquidity when the utilization rate is high, because the dealer intermediation capacity then is limited. The signed volume is suited to measure the dealer balance sheet utilization rate because dealers take the opposite position of trades: the demand side of the market initiates all trades and determines if the market is dominated by buyers or sellers. Thus, if trading mostly goes in one direction (i.e. the absolute value of signed volume is high), the dealers are forced to take large positions in the opposite direction which reduces their balance sheet capacity. As expected, a higher signed volume decreases the number of dealers and increases volatility.

Finally, table IV tests Prediction 5 by showing that the dealer number-to-volatility ratio decreases when dealer constraints go up, i.e., when (i) margins go up, or (ii) capital ratio goes down, or (iii) signed volume goes up.

[Insert Table II, III and IV here]

D.1. Open Interest

Another potential explanation to why liquidity recently has diminished even when volatility is low, is that the demand for liquidity simply could be lower. We can estimate this through the open interest which counts the number of active futures contracts in the market. Figure 8 shows that total open interest is around 3 million. It was slowly increasing from 2009 to 2018 and have been

slightly decreasing since. However, this decrease is not nearly as large as the drop in market depth and the open interest does not exhibit large downwards jumps like the depth. Therefore, the open interest to depth ratio is significantly lower today compared to before 2018. It is not lower open interest that has caused market depth to decrease, but on the contrary, it appears that open interest has decreased in response to the lower depth. Splitting the open interest by trader type, Figure A.2 of the Internet Appendix shows that asset managers and leveraged funds has fewer outstanding contracts today. The drop in asset managers started in 2018 while leveraged funds have been decreasing since 2015. Surprisingly, the number of traders has not decreased as much and it has even increased for asset managers.

[Insert Figure 8 here]

E. Dealer numbers and Returns

This section explores the relationship between the dealer number and returns of the E-mini. Prediction 6 states that there should be a positive relationship between dealer numbers and contemporaneous returns, and a negative relationship between dealer numbers and expected future returns. To test this, we estimate the exposure of returns to the dealer number according to

$$R_t^{period} = \alpha + \beta N_t + \epsilon_t, \quad (21)$$

$$\text{and } R_t^{period} = \alpha + \beta N_{t-1} + \epsilon_t, \quad (22)$$

where R_t^{period} is the return of the E-mini for a given trading period on day t and N_t is the number of dealers on day t . Figure 9 plots the cumulative daily returns for the E-mini contract during our sample period (CTC) and also the daily returns split into the overnight period (CTO) and U.S. opening hours period (OTC). The overnight period has lower trading volume but CTO returns make up the largest portion of total daily CTC returns as documented by Boyarchenko, Larsen, and Whelan (2023).

[Insert Figure 9 here]

Table V reports regression coefficients and, as expected, we find a positive contemporaneous relationship between returns and dealer numbers: when fewer (more) dealers offer liquidity by posting limit orders, returns are lower (higher). This holds for close-to-close (CTC) returns as well as

close-to-open (CTO) and open-to-close (OTC) returns. Here, open and close are defined according to the open and close of U.S. equity markets which is at 9:30 ET and 16:15 ET, respectively. Because the E-mini trading day officially starts in the U.S. evening, this definition of open and close implies that, on any trading day t , the CTO period comes first and is then followed by the OTC period.

Combining Prediction 1 and 6 implies that volatility and price return have a negative contemporaneous correlation in our model. A negative correlation between returns and volatility have historically been referred to as the ‘leverage effect’ due to Black (1976): a decrease in a firm’s stock price leads to a higher debt-to-equity ratio because the value of debt remains constant, and when a firm becomes more leveraged, it is more risky to invest in, i.e., volatility is higher. The negative return-volatility correlation have been documented empirically in several studies across various countries and markets, but it has been deemed unlikely that it solely is explained by the debt-to-equity ratio. For example, changes to the capital structure of firms have been shown not to affect volatility. Furthermore, the negative correlation is also observed in other markets such as commodity and currency markets. Our model offers a novel liquidity-driven argument to the leverage effect: when dealers becomes more constrained and the dealer number decrease, expected returns go down and at the same time volatility increases.

[Insert Table V here]

Finally, we test if returns are predicted by the dealer number as suggested by our model. Table V shows that the dealer number on trading day $t - 1$ has a negative, albeit not highly significant, effect CTC returns on day t . However, focusing on the first part of the trading day – the CTO period – we see a significant effect. This suggests that the predictability is stronger when moving to a higher sampling frequency. The predictability results from table V remains when controlling for the return on the previous trading day and the dealer number therefore provides a liquidity-based rationale for the negative first order autocorrelation that is observed in daily returns (and in returns at higher frequencies). Due to autocorrelation, standard errors and confidence intervals are computed using a block bootstrap. Figure 10 depicts the distributions of the 2 β coefficients for the daily CTO returns regressed on 1) the dealer number on the same trading day, and 2) the dealer number of the preceding trading day.

[Insert Figure 10 here]

F. Alternative Liquidity Measures

We now compare the dealer number and market depth to other classical measures of (il)liquidity. The simplest illiquidity measure is the bid–ask spread as it is directly measurable from prices and available in real time. Glosten and Milgrom (1985) show that the spread is increasing in asymmetric information, and liquidity providers therefore require a higher spread when market participants have private information. Unfortunately, it is most often futile to use the spread for measuring liquidity of high volume exchange-traded contracts like the E-mini, because the minimum price change unit (the tick) acts as an effective minimum to the spread. The E-mini tick size is 0.25 index points = USD 12.5, and Figure 11 shows that the spread is almost always equal to the tick, rendering it useless as a continuous liquidity measure. Instead, the spread can be used as an indicator of large liquidity shocks, where a spread larger than 1 tick indicates a substantial illiquidity. Examples of this is seen in panel (b) of Figure 11 where the spread increased to two ticks during the Global Financial Crisis in 2009 and in the COVID-19-related stock market crash in 2020.

Besides the spread, we also consider Kyle’s lambda (see Kyle (1985)) and Amihud’s illiquidity measure (see Amihud (2002)) which both measure market impact, i.e., how much trading activity causes price movements. Panels (d) and (f) of Figure 11 show that market impact has indeed been higher since 2020. A significant drawback of Amihud’s illiquidity measure and Kyle’s lambda compared to market depth is that they are not measurable in real time; they require a period to be measured over. This is disadvantageous to traders in high frequency markets, where conditions can change almost instantaneously.

[Insert Figure 11 here]

Market depth is by definition almost equal to the standard definition of liquidity: a large depth means that market participants instantaneously can buy or sell a large amount of the asset without affecting its price. As discussed, the long-run depth of the E-mini is driven by the dealer number, suggesting that the dealer number is a fundamental component of market liquidity. This is confirmed in table VI which shows that depth explains 76% of variation in the dealer number (and vice versa). The table also shows that the traditional liquidity measures have very little explanatory power on the dealer number, suggesting that the dealer number contains unique information on market fundamentals such as volatility. To confirm this, we show in table VII that the dealer number maintains explanatory power against volatility when controlling for classical liquidity measures.

Table VIII shows correlations of changes in the liquidity measures and volatility, trading volume and returns. Depth and dealer number are highly correlated while the traditional liquidity measures have high correlation amongst themselves but not with depth and liquidity. The traditional liquidity measures have a higher absolute correlation with volatility compared to the dealer number but their correlation to overall trading volume and to returns are insignificant.

[Insert Table VI, VII and VIII here]

G. Market Design

Liquidity drops when fewer market participants post limit orders. This typically happens when risk is high. To avoid liquidity dry-ups, most markets have designated market makers that always supply liquidity. Surprisingly, this is not the case for the E-mini and the market depth can therefore potentially go to zero. In practice, there are a few market participants that act as de facto market makers. These are high frequency traders such as Citadel that post limit orders on both sides and all levels of the order book. The HF traders earn their profit through the bid-ask spread, but they will quickly cancel limit orders on one side of the LOB if trading starts being one-directional. Thus, their role as market makers is questionable. The lack of designated market makers is therefore a potential contributing factor to the lowered depth of the E-mini: the risk of being the last remaining liquidity provider could cause a Nash equilibrium where everyone stops posting limit orders to avoid being the one left holding the baby.

IV. Conclusion

This paper investigates market depth and dealer numbers in exchange-traded markets. Empirically, we document that depth in the S&P 500 E-mini futures contract has decreased by 80% in recent years, and that this is driven by the number of liquidity providers (dealers) decreasing, whereas the average dollar volume offered per dealer is stationary. To explain this liquidity dry-out, we introduce a market microstructure model in the spirit of Grossman and Miller (1988). Novel to our model, we endogenize the number of dealers and we introduce trading costs for dealers in the form of an entry cost to participate in trading and also a margin requirement. The entry cost reflects the setup expenses in form of computers and employees etc. that large financial institutions incur if they want to act as market makers. The margin requirement is an integral part of how central

exchanges function, and it acts to effectively remove counterparty credit risk, but at the same time it implies that market participants must tie up capital when initiating a position in the market.

From the model, we obtain the following testable predictions. Firstly, there is a negative relationship between volatility and liquidity (measured as the number of dealers). Secondly, higher margins and lower dealer wealth lead to lower dealer numbers and higher volatility. Thirdly, when participation gets more costly, the volatility-liquidity curve shifts downwards. Finally, there is a positive relationship between dealer numbers and contemporaneous returns, and a negative relationship between dealer numbers and expected future returns.

Empirically, we confirm that liquidity and volatility are negatively correlated – liquidity drops when volatility increases. Next, we show that large volatility spikes can have a lasting effect on liquidity as seen in figure 3. Particularly, we find that the February 2018 VIX spike (volmageddon) and the 2020 COVID-19 market crash both resulted in a permanent drop in liquidity. Figure 5 further illustrates this by plotting the volatility-liquidity relationship and highlighting that for a given level of volatility, liquidity measured as number of dealers is significantly lower from 2018 and onwards compared to earlier years.

To rationalize the recent low liquidity-to-volatility ratio, we consider margins as a proxy for participation costs, and find that, in accordance with our model, they have increased in recent years. Specifically, we show that volatility affects future margins, creating a feedback effect where volatility spikes increase margins for prolonged periods and, in turns, the margin increases lead to lower liquidity even after volatility normalizes.

We also confirm that the dealer number explain returns. Contemporaneously, returns and the dealer number are positively correlated, and one period apart, the relationship is negative.

Novel to the literature, we show that the number of dealers in a market is central when measuring liquidity. The dealer number functions both as an independent liquidity measure, but it also adds additional information to market fundamental such as volatility when controlling for classical liquidity measures like the bid-ask spread and market impact.

The large drop in the depth, caused by fewer dealers in the S&P 500 E-mini futures market, shows that even the most traded assets are prone to liquidity risk. A fraction of dealers leaving the market could be more critical compared to all dealers lowering their offered liquidity – in a game theory setup dealers want to avoid be the only one left offering liquidity. This raises the question of whether exchange traded markets are properly designed. For example, the S&P 500 E-mini futures

market does not have any designated market makers. This is unlike e.g. the 10-year U.S. Treasury futures market that does have designated market makers which provide security against a complete liquidity dry-up: in this market, we also observe large volatility spikes and margin increases, but they do not cause lasting decreases in the liquidity.

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V. Figures

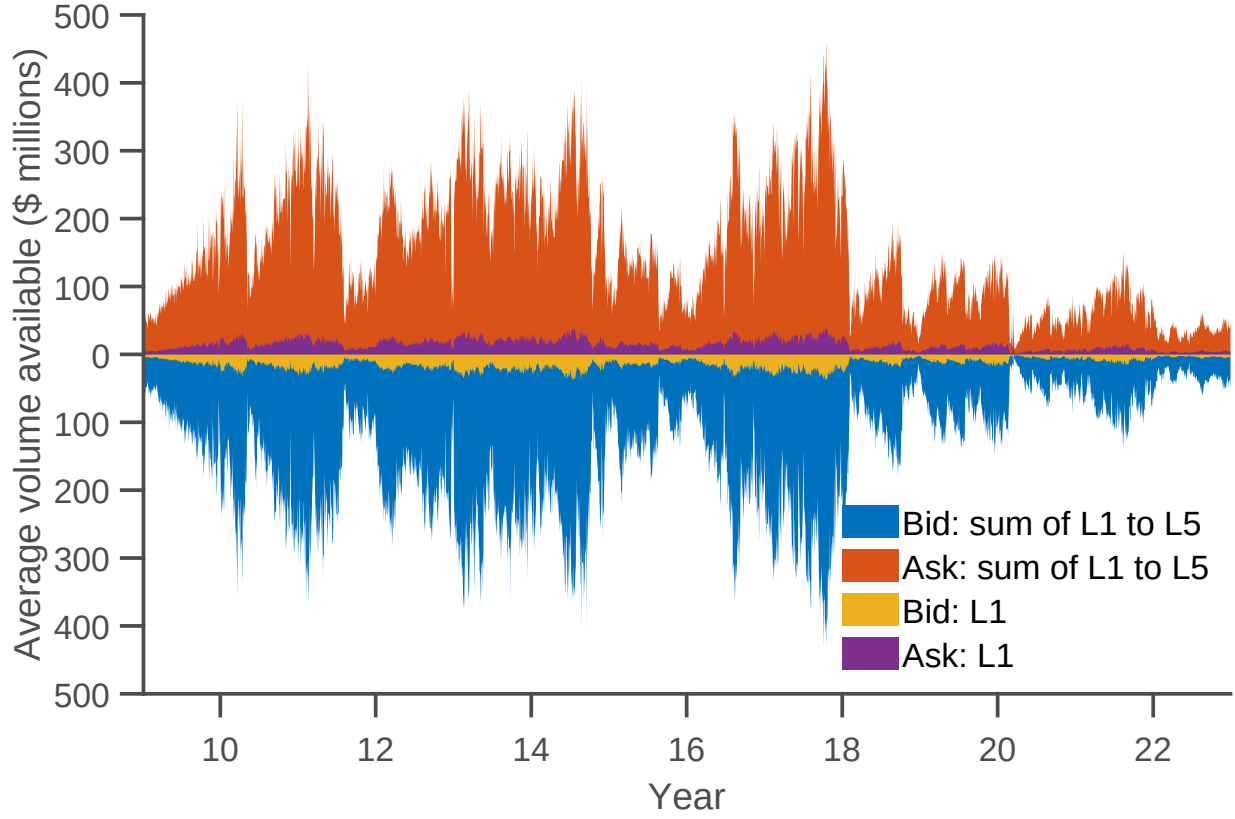
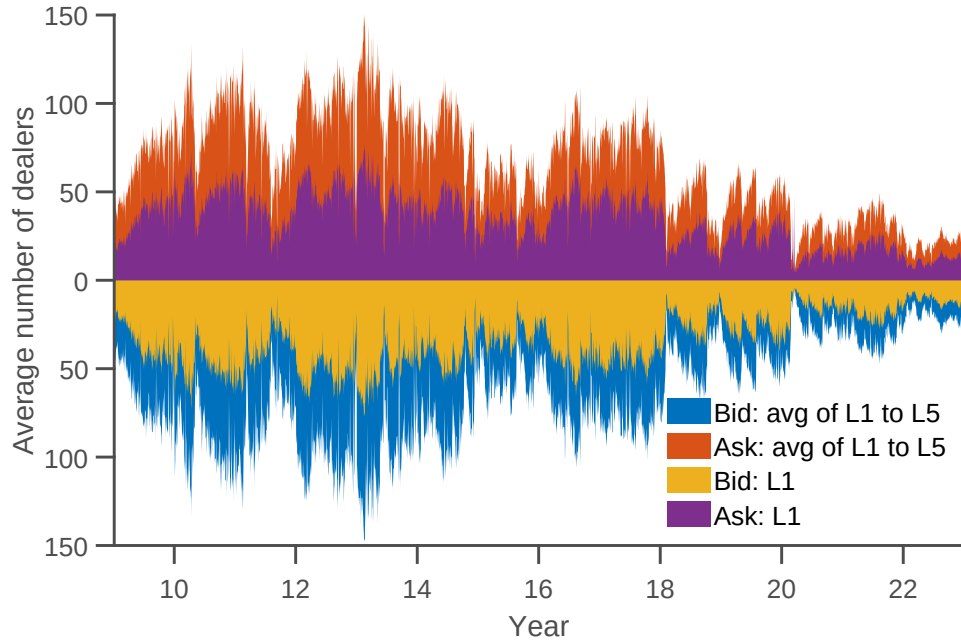
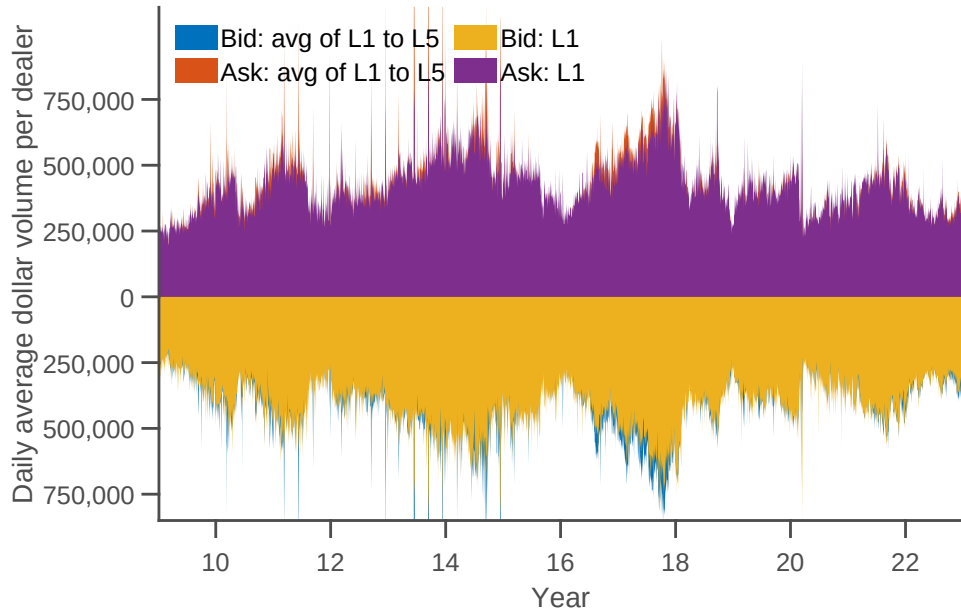


Figure 1. Time series of dollar volume

The figure plots the time series of market depth measured as dollar volume available at level 1 and at level 1 to 5 of the limit order book for the S&P 500 E-mini futures contract. The daily dollar volume is measured as averages of 5-minute samples throughout the trading day. The sample period is January 2009 to December 2022.



(a)



(b)

Figure 2. Time series of dealer number and liquidity per dealer

Figure (a) plots the time series for the number of dealers at level 1 of the order book and for the average number of dealers at level 1 to 5. Figure (b) plots the time series of the average daily liquidity offered per dealer. Liquidity is measured as the average dollar volume offered per dealer. The daily dealer number and dollar volume per dealer are measured as averages of 5-minute samples throughout the trading day. The sample period is January 2009 to December 2022.

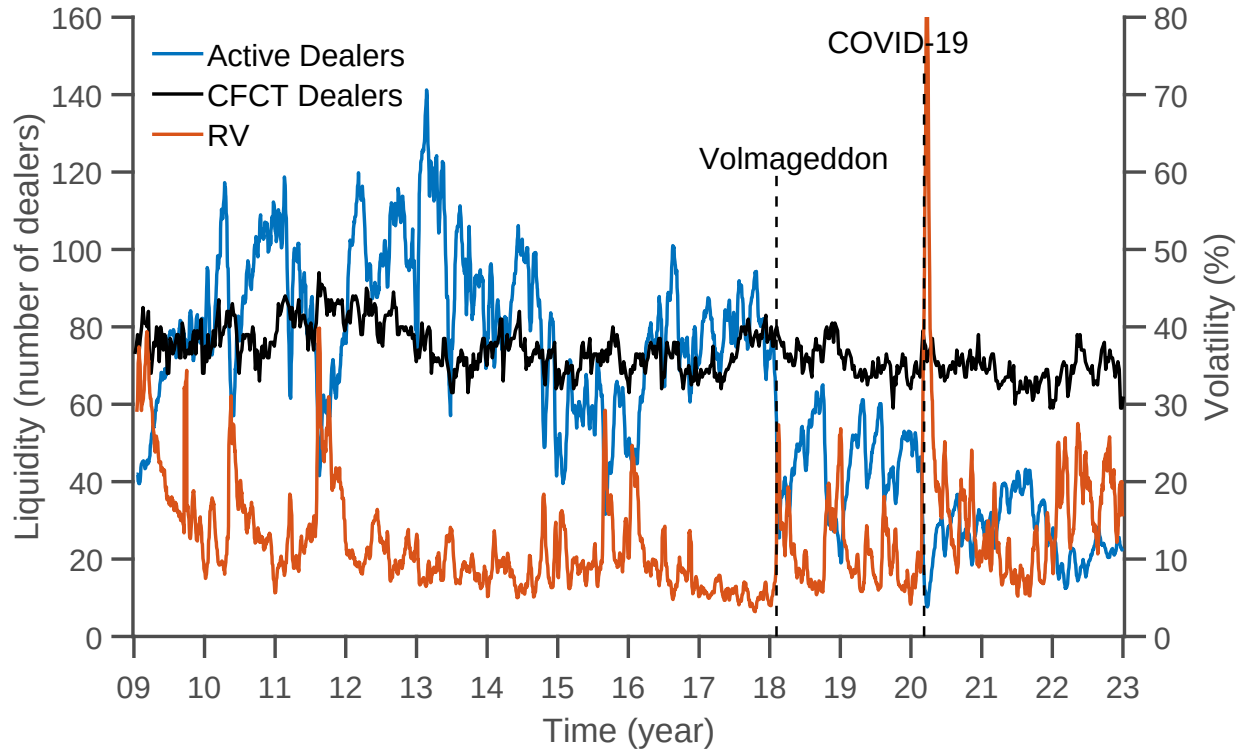
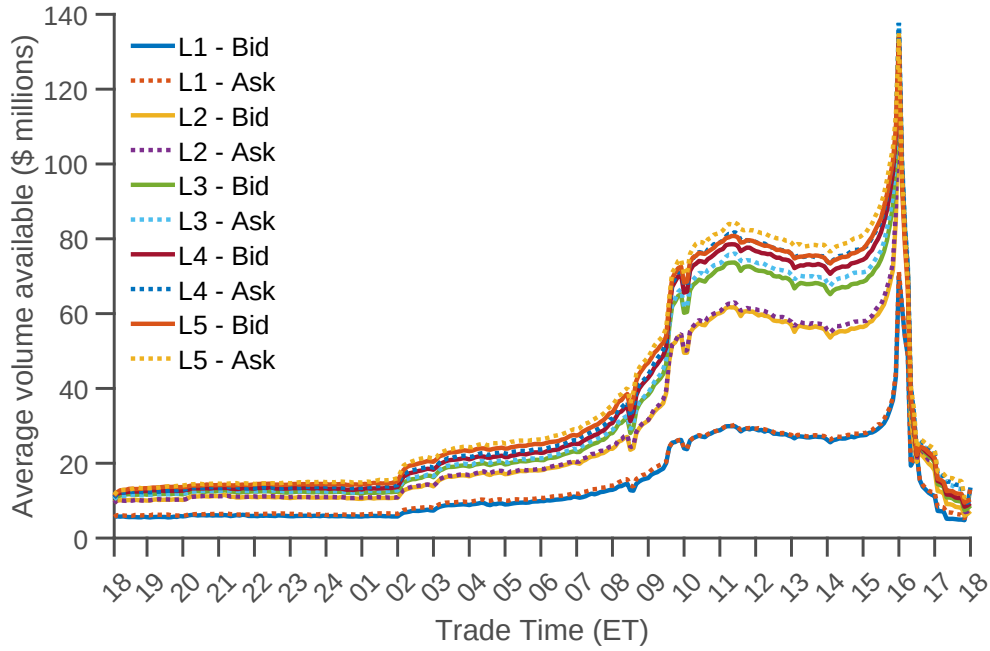
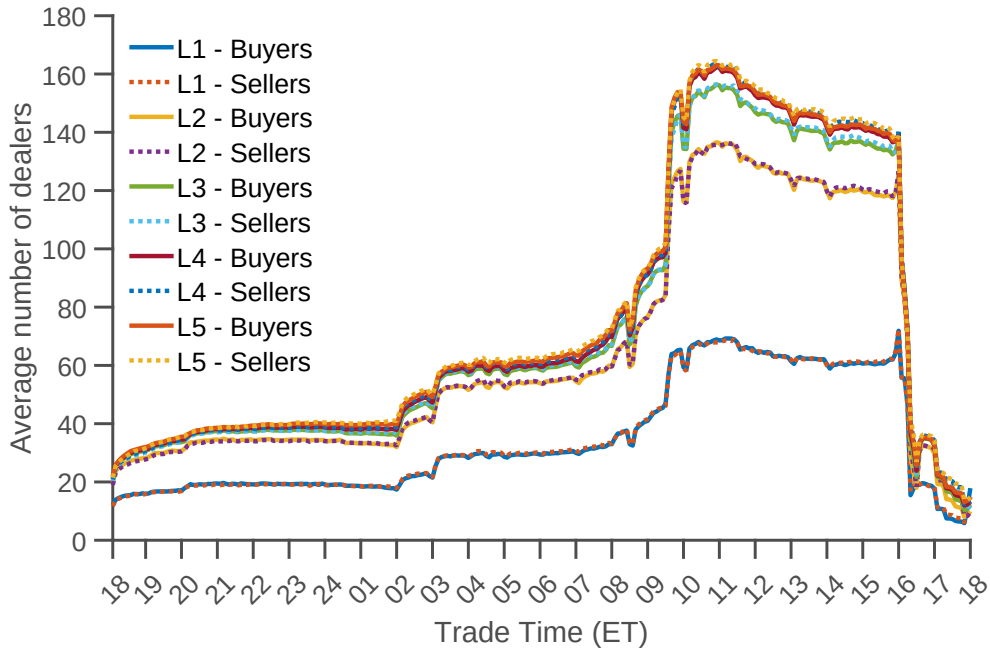


Figure 3. Time series of dealer number and volatility

The figure plots the time series of 1) the average daily number of active dealers (i.e. dealers that are posting limit orders) across level 1 to 5 of the LOB for the S&P 500 E-mini futures contract, 2) the number of registered CFTC dealers (computed as long plus short positions), and 3) the (annualized) daily realized volatility computed from 5-minute log returns. All variables are computed as a 10 day rolling average to reduce noise. The sample period is January 2009 to December 2022.



(a)



(b)

Figure 4. Intraday liquidity and dealer number

Figure (a) plots the intraday average market depth measured as dollar volume available for level 1 to 5 of the order book for the S&P 500 E-mini futures contract. Figure (b) plots the intraday average number of dealers for level 1 to 5 of the order book. The dollar volume and dealer number are measured at a 5 minute frequency throughout the trading day. The sample period is January 2009 to December 2022.

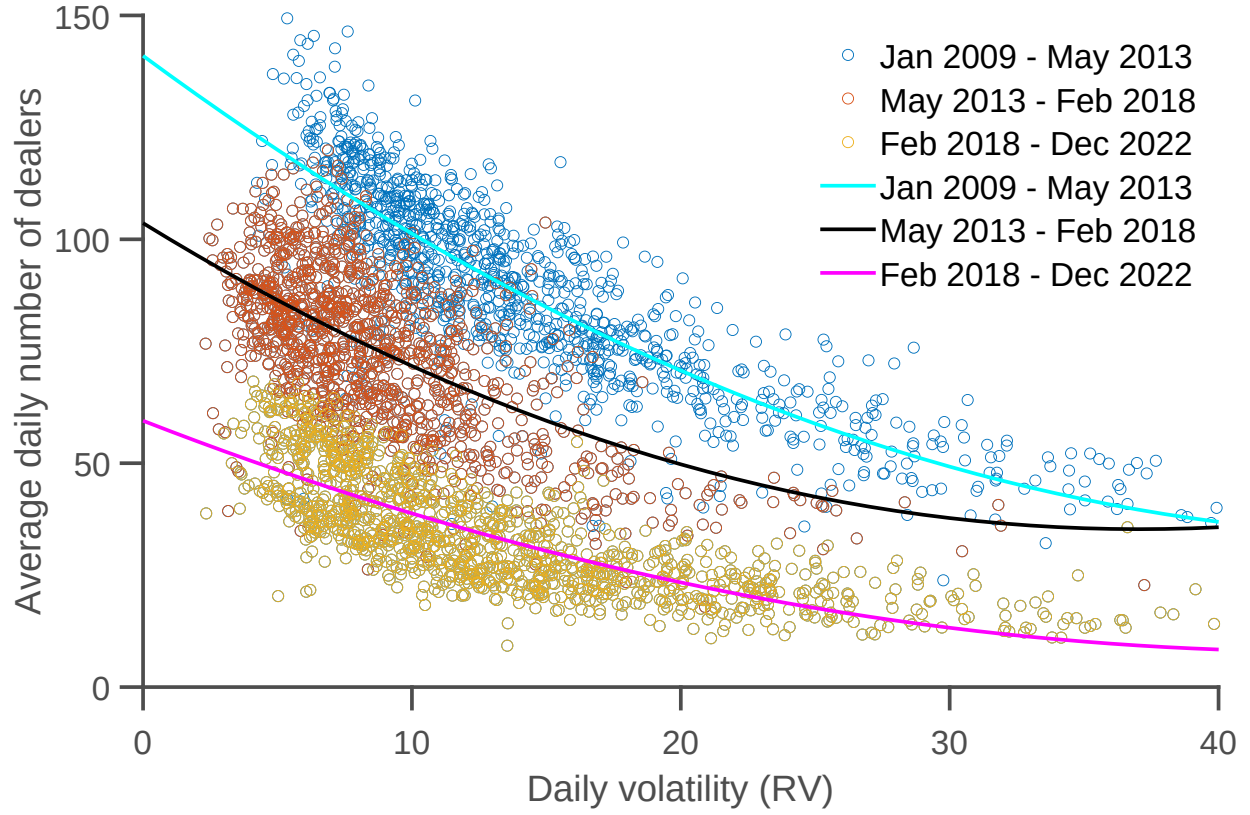
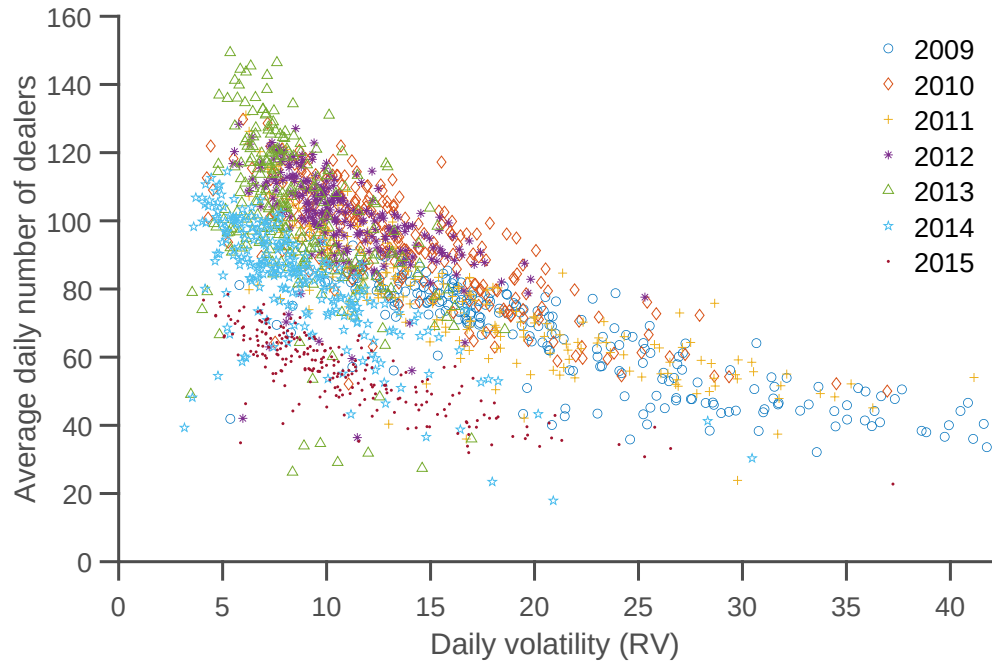
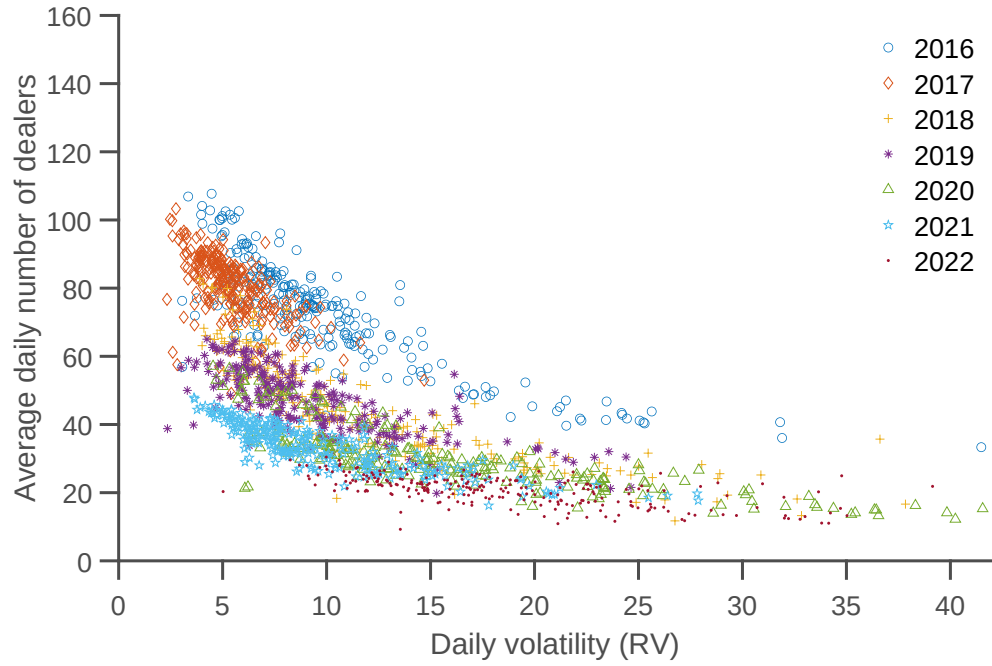


Figure 5. Scatter plot of volatility and number of dealers

The figure is a scatter plot of the relationship between volatility (computed as the annualized daily realized volatility from 5-minute log returns) and the average daily number of dealers (computed as the average across level 1 to 5 of the LOB) for the S&P 500 E-mini futures contract. The lines plot a quadratic regression of dealer number on the volatility. The sample period is January 2009 to December 2022.



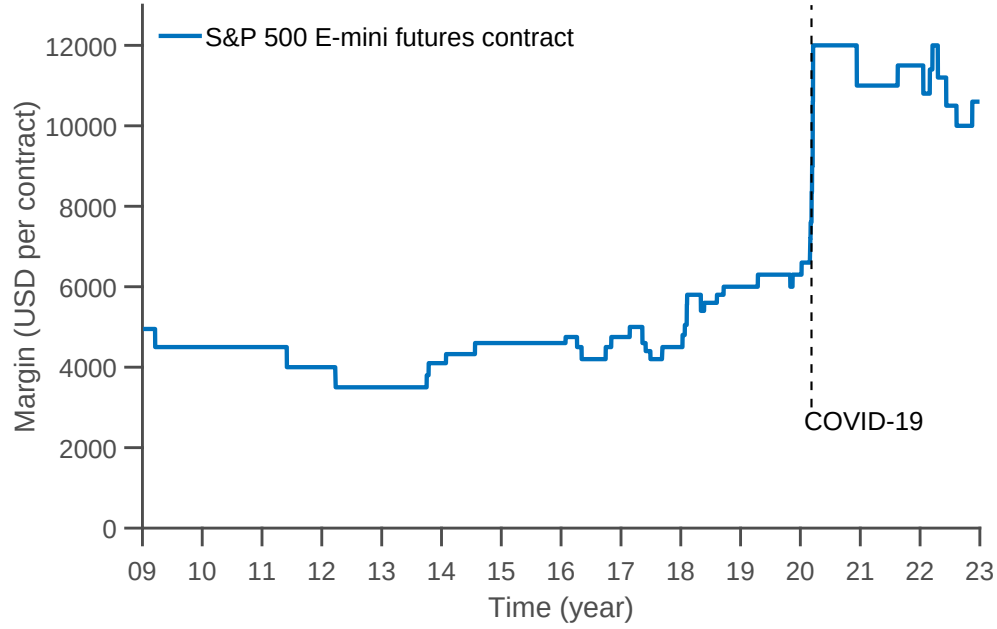
(a)



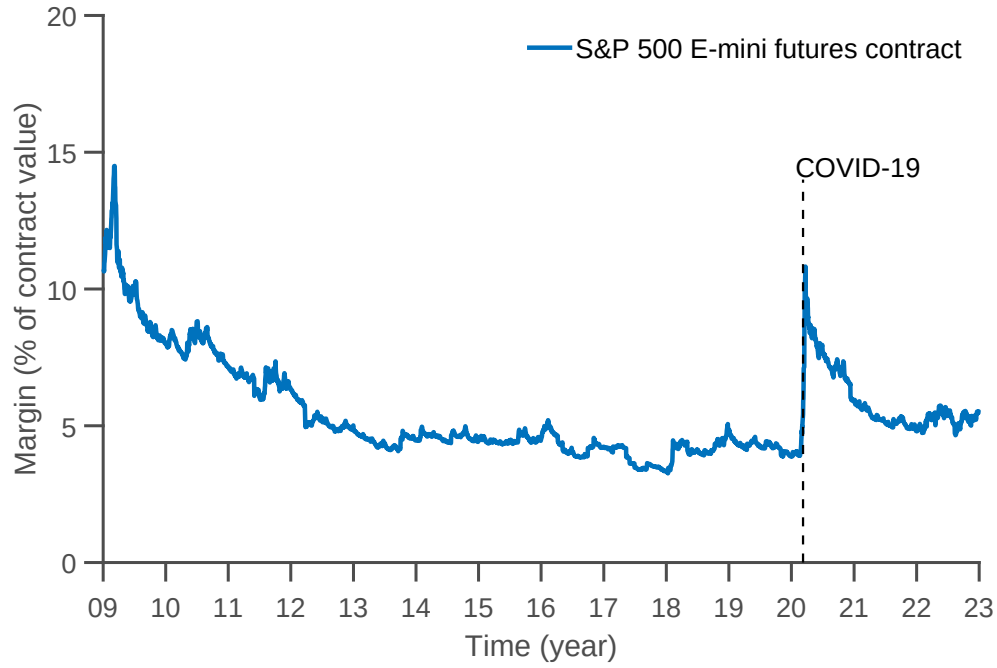
(b)

Figure 6. Scatter plot of volatility and number of dealers by year

The figure is a scatter plot of the relationship between the volatility (computed as the annualized daily realized volatility from 5-minute log returns) and the average daily number of dealers (computed as the average across level 1 to 5 of the LOB) for the S&P 500 E-mini futures contract. Figure (a) shows the years 2009 to 2015 and figure (b) shows the years 2016 to 2022.



(a)



(b)

Figure 7. Time series of futures margin

The figure plots the time series of the margin for the S&P 500 E-mini futures contract. (a) is the margin in U.S. dollars and (b) is the margin percentage, i.e., the margin relative to the current value of the E-mini contract. The sample period is January 2009 to December 2022.

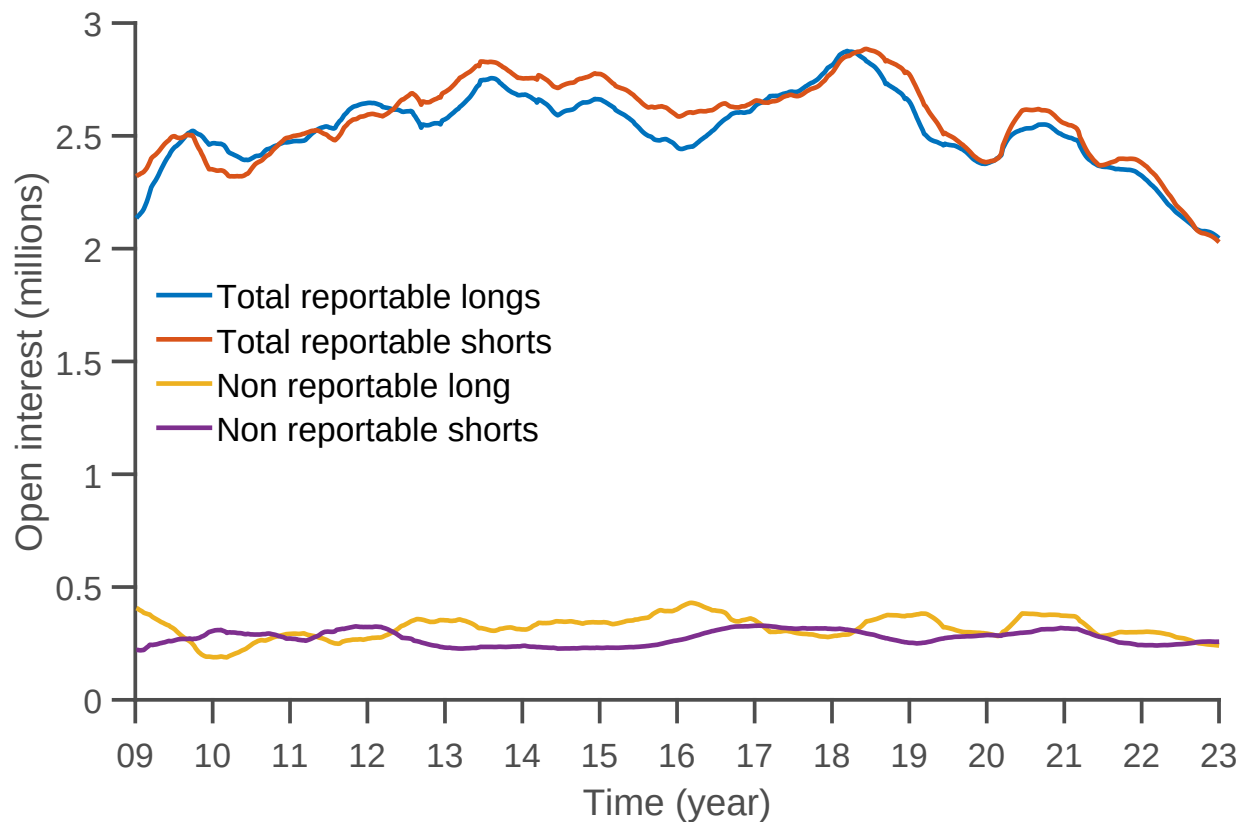


Figure 8. Time series of open interest

The figure plots the time series of the open interest for the S&P 500 E-mini futures contract. Open interest is the total number of futures contracts held by market participants at the end of the trading day. Open interest is calculated by adding all the contracts from opened trades and subtracting the contracts when a trade is closed. Open interest and trading volume are related concepts, with the key difference being that volume counts all contracts that have been traded, while open interest is a total of contracts that remain open in the market. Traders interpret open interest as the cash flowing to the market: as open interest increases, more money is moving into the futures contract, and as open interest declines money is moving out of the market. The sample period is January 2009 to December 2022.

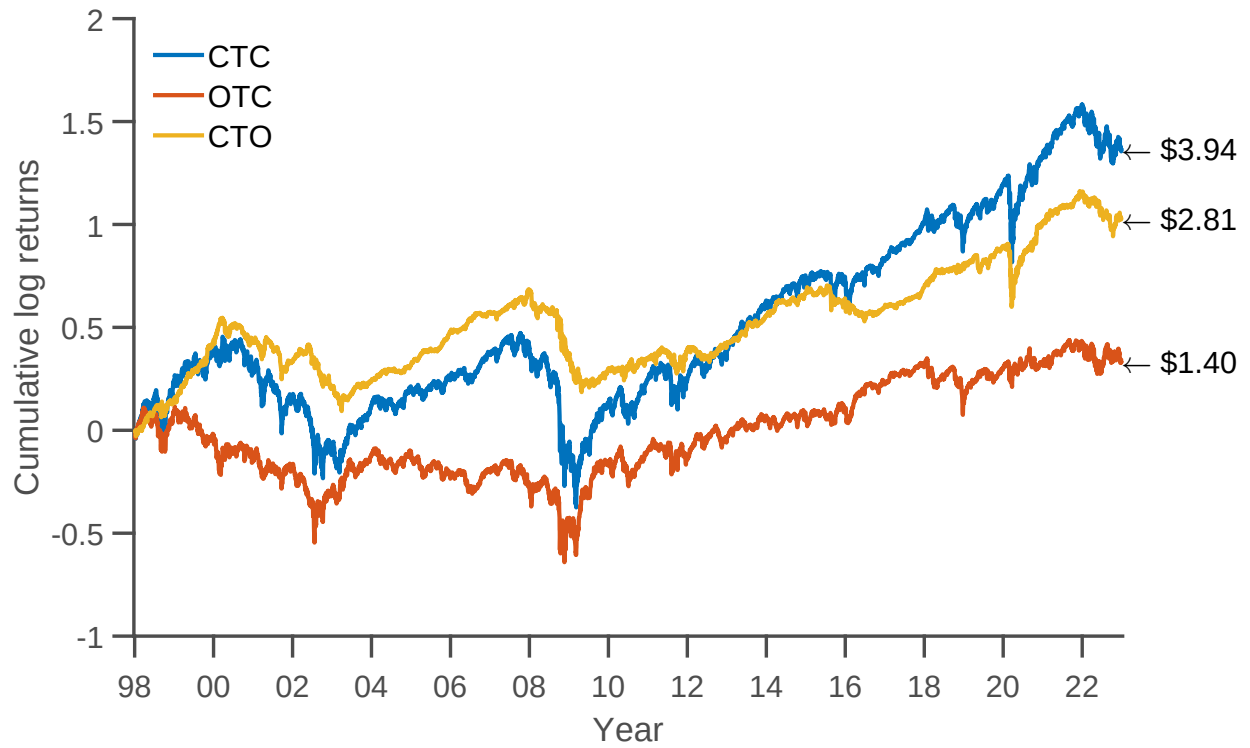


Figure 9. Time series of returns for the S&P 500 futures contract

The figure plots the time series of close-to-close, open-to-close and close-to-open log returns for the S&P 500 futures contract. Opening prices are sampled at 9:30 ET and closing prices are sampled at 16:15 ET. Between 1998.1 and 2004.4, returns are computed from the value weighted average prices (VWAPs) of the original S&P 500 futures contract and sourced from Refinitiv. From 2004.1 (when the E-mini became the most liquid futures contract traded on the SPX index) and until the end of the sample in 2022.12, returns are computed from the VWAPs of the E-mini contract.

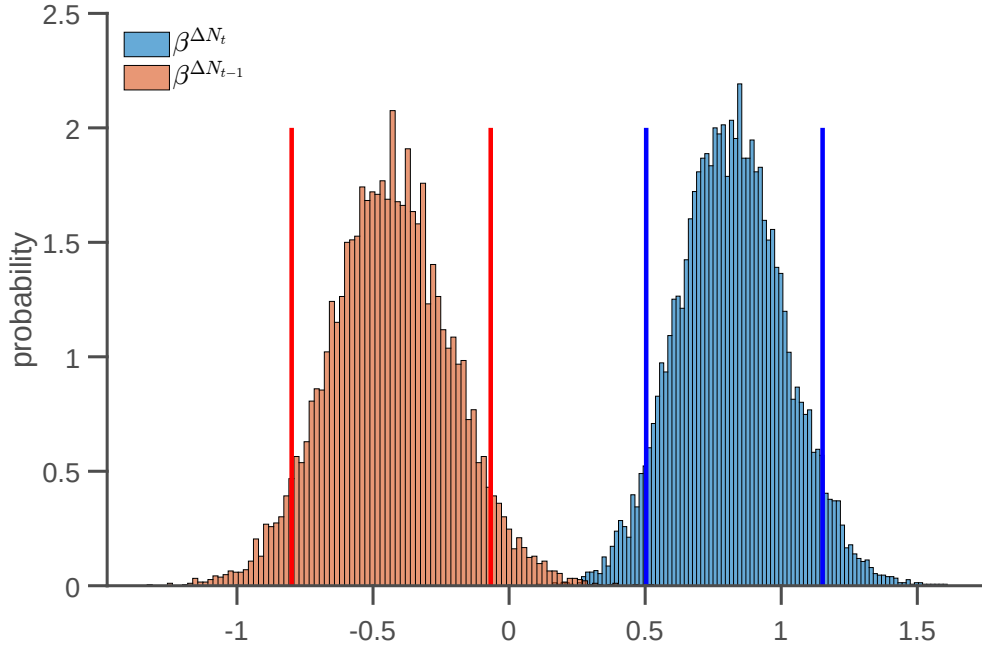


Fig-

ure 10. Distribution of CTO return β s from the bootstrapped estimates in table V

The figure plots the distributions of the regression coefficients β^{N_t} and $\beta^{N_{t-1}}$ for the regressions of CTO returns on the dealer number: $R_t^{CTO} = \alpha + \beta N_t + \epsilon_t$ and $R_t^{CTO} = \alpha + \beta N_{t-1} + \epsilon_t$. The sample period is January 2009 to December 2022.

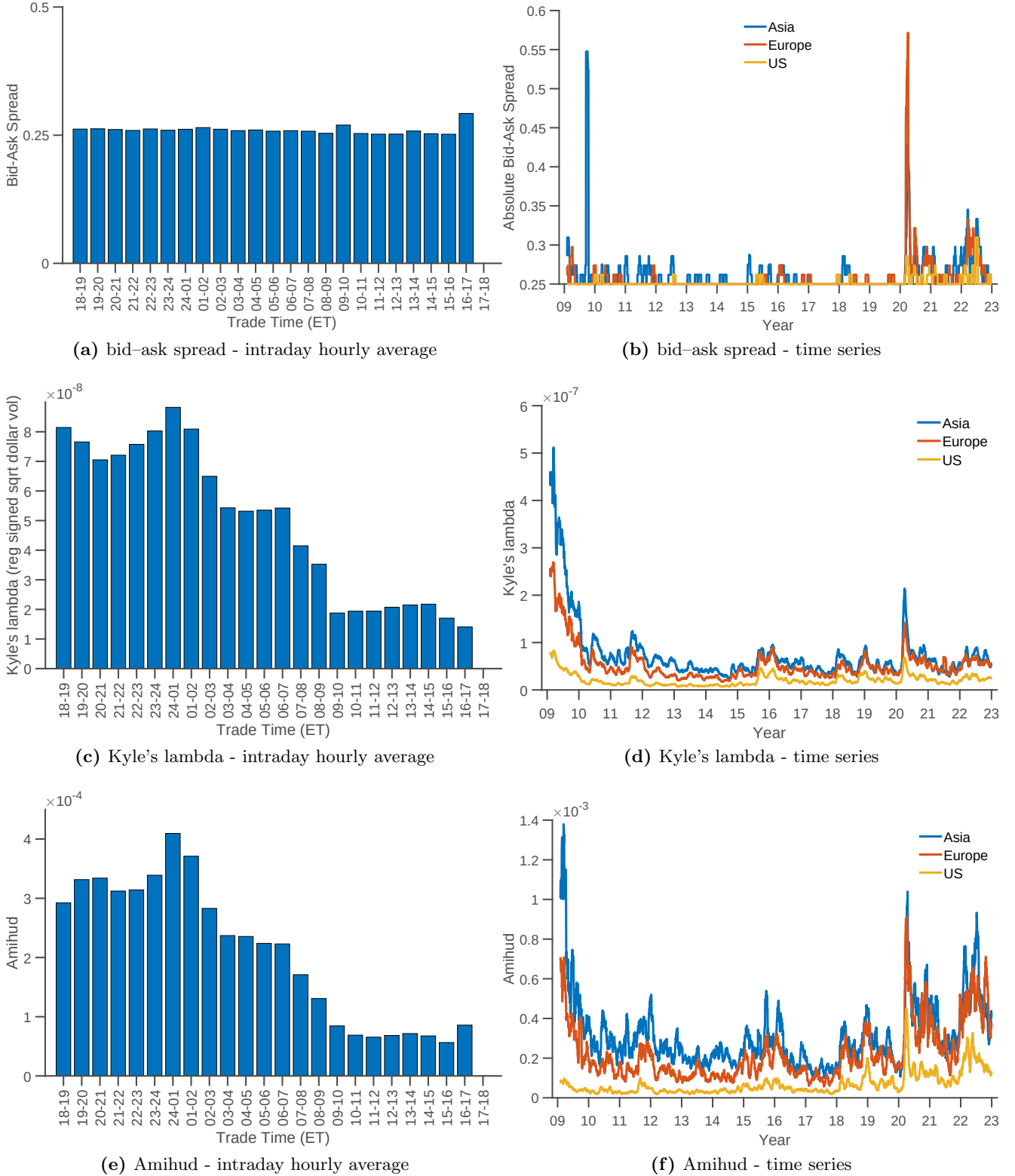


Figure 11. Alternative liquidity measures

Figure (a) and (b) plots the bid-ask spread. (c) and (d) plots Kyle's lambda, and (e) and (f) plots Amihud's illiquidity measure defined as $1/N \sum_{i=1}^N |r_i|/\$V_i$, where N is the number of observations, r_i is the return and $\$V$ is the dollar trading volume. Kyle's lambda and Amihud are computed at an hour frequency based of 1-minute sampling. Plots of intraday averages show the averages of a given trading hour across all trading days in the sample period. All time series are plotted as rolling monthly averages of daily estimates to reduce noise. The sample period is January 2009 to December 2022.

VI. Tables

	(i)	(ii)	(iii)	(iv)	(v)
$\Delta\sigma_t$	-0.53 (0.09)		-1.19 (0.14)		-1.16 (0.14)
$\Delta\sigma_t^2$		-0.31 (0.10)	0.93 (0.16)		0.93 (0.16)
$\Delta\kappa_t$				-14.37 (5.05)	-6.66 (2.72)
α	-0.01 (0.03)	-0.00 (0.04)	-0.01 (0.03)	-0.02 (0.04)	-0.02 (0.03)
$R^2(\%)$	10.29	2.44	15.84	2.11	16.27

Table I. The relationship between the dealer number, volatility and margins

This table considers the contemporaneous relationship between the dealer number, volatility and margins for the S&P 500 E-mini futures contract. The dependent variable is the change in dealer number on day t which is measured as the change in the average daily number of dealers, N_t , at level 1 to 5 of the LOB. The explanatory variables are changes to volatility (and/or variance) on day t which is measured using daily realized variance computed from 5-minute log returns, and the change in the margin percent, $\Delta\kappa_t$, which is the USD margin requirement in percent of the E-mini contract value. The sample period is January 2009 to December 2022. The regression specifications are

$$\begin{aligned}
(i) \quad & \Delta N_t = \alpha + \beta \Delta\sigma_t + \epsilon_t, \\
(ii) \quad & \Delta N_t = \alpha + \beta \Delta\sigma_t^2 + \epsilon_t, \\
(iii) \quad & \Delta N_t = \alpha + \beta_1 \Delta\sigma_t + \beta_2 \Delta\sigma_t^2 + \epsilon_t, \\
(iv) \quad & \Delta N_t = \alpha + \beta \Delta\kappa_t + \epsilon_t, \\
(v) \quad & \Delta N_t = \alpha + \beta_1 \Delta\kappa_t + \beta_2 \Delta\sigma_t + \beta_3 \Delta\sigma_t^2 + \epsilon_t.
\end{aligned}$$

Standard errors are estimated using a Newey and West (1987) correction with lags selected following Lazarus, Lewis, Stock, and Watson (2018). The sample period is January 2009 – December 2022.

	(i)	(ii)	(iii)	(iv)	(v)
σ	-0.41 (0.10)				-0.58 (0.13)
margin %		0.05 (0.15)			-0.10 (0.20)
capital ratio			-0.24 (0.14)		-0.55 (0.19)
signed volume				-0.27 (0.05)	-0.02 (0.05)
$R^2(\%)$	16.74	0.28	5.75	7.24	36.79

Table II. The dealer number and dealer constraints

This table considers the daily number of dealers regressed on daily dealer constraints for the S&P 500 E-mini futures contract. Dealer constraints are measured using the margin percentage, capital ratio, and signed trading volume. We control for the volatility, σ , in the multiple regression. All variables are z-scored. Standard errors are estimated using a block bootstrap with 10,000 draws and where the optimal block size is chosen in a data driven way following Patton, Politis, and White (2009). The sample period is January 2009 – December 2022.

	(i)	(ii)	(iii)	(iv)	(v)
N	-0.41				-0.41
	(0.09)				(0.05)
margin %		0.41			0.07
		(0.08)			(0.08)
capital ratio			-0.40		-0.39
			(0.09)		(0.08)
signed volume				0.56	0.37
				(0.08)	(0.09)
$R^2(\%)$	16.74	16.70	16.27	31.29	55.61

Table III. Volatility and dealer constraints

This table considers daily volatility regressed on daily dealer constraints for the S&P 500 E-mini futures contract. Dealer constraints are measured using the margin percentage, the capital ratio, signed trading volume. We control for the dealer number, N in the multiple regression. All variables are z-scored. Standard errors are estimated using a block bootstrap with 10,000 draws and where the optimal block size is chosen in a data driven way following Patton, Politis, and White (2009). The sample period is January 2009 – December 2022.

	(i)	(ii)	(iii)	(iv)
margin %	-0.30			-0.24
	(0.11)			(0.15)
capital ratio		0.21		-0.01
		(0.13)		(0.18)
signed volume			-0.35	-0.29
			(0.06)	(0.05)
$R^2(\%)$	9.00	4.45	11.94	17.09

Table IV. Dealer number-to-volatility ratio and dealer constraints

This table considers the daily dealer number-to-volatility ratio regressed on daily dealer constraints for the S&P 500 E-mini futures contract. Dealer constraints are measured using the margin percentage, capital ratio, and signed trading volume. All variables are z-scored. Standard errors are estimated using a block bootstrap with 10,000 draws and where the optimal block size is chosen in a data driven way following Patton, Politis, and White (2009). The sample period is January 2009 – December 2022.

	CTC	CTC	CTO	CTO	OTC	OTC
β^{N_t}	1.68		0.80		0.89	
	(0.33)		(0.20)		(0.28)	
	[1.19, 2.28]		[0.50, 1.15]		[0.44, 1.36]	
$\beta^{N_{t-1}}$		-0.52		-0.41		-0.10
		(0.35)		(0.22)		(0.28)
		[-1.18, -0.06]		[-0.81, -0.08]		[-0.57, 0.34]
$R^2(\%)$	0.87	0.25	0.59	0.29	0.53	0.19

Table V. Liquidity betas: returns regressed on the dealer number

This table shows the coefficients for regressions of the types $R_t^{period} = \alpha + \beta N_t + \epsilon_t$ or $R_t^{period} = \alpha + \beta N_{t-1} + \epsilon_t$, where R_t^{period} the return over a given trading period on day t and N_t is the number of dealers on day t . Standard errors and 95% confidence intervals are estimated using a block bootstrap with 10,000 draws and where the optimal block size is chosen in a data driven way following Patton, Politis, and White (2009). We consider the close-to-close (CTC) period, the close-to-open (CTO) period and the open-to-close (OTC) period, where we define the close as 16:15 ET and the open as 9:30 ET, according to the close and open of U.S. equity markets. This implies that the overnight period (i.e. CTO) comes before the CTO period on all trading day for the E-mini. The regressions have yearly time fixed effects and the sample period is January 2009 – December 2022.

	(i)	(ii)	(iii)	(iv)	(v)
depth	0.87				0.87
	(0.09)				(0.08)
Kyle's λ		-0.16			0.22
		(0.36)			(0.08)
Amihud illiq			-0.19		-0.04
			(0.13)		(0.03)
BA spread				-0.32	-0.19
				(0.20)	(0.04)
$R^2(\%)$	76.49	2.70	3.54	10.39	79.72

Table VI. The dealer number and traditional liquidity measures

This table considers the daily number of dealers regressed on traditional liquidity measures for the S&P 500 E-mini futures contract. Liquidity is measured using (i) the market depth (measured as the available dollar volume), (ii) Kyle's λ , (iii) Amihud's (2002) illiquidity measure, and (iv) the bid-ask spread. All variables are z-scored. Standard errors are estimated using a block bootstrap with 10,000 draws and where the optimal block size is chosen in a data driven way following Patton, Politis, and White (2009). The sample period is January 2009 – December 2022.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
N	-0.41 (0.09)					-0.26 (0.08)
Kyle's λ		0.64 (0.36)			0.44 (0.31)	0.46 (0.28)
Amihud illiq			0.41 (0.12)		-0.03 (0.07)	-0.04 (0.06)
BA spread				0.61 (0.10)	0.35 (0.14)	0.27 (0.14)
$R^2(\%)$	16.74	41.20	17.13	37.28	48.51	54.38

Table VII. Volatility and traditional liquidity measures

This table considers daily volatility regressed on daily liquidity for the S&P 500 E-mini futures contract. Liquidity is measured using (i) the number of dealers N , (ii) Kyle's λ , (iii) Amihud's (2002) illiquidity measure, and (iv) the bid-ask spread. All variables are z-scored. Standard errors are estimated using a block bootstrap with 10,000 draws and where the optimal block size is chosen in a data driven way following Patton, Politis, and White (2009). The sample period is January 2009 – December 2022.

	2	3	4	5	6	7	8
1: ΔN	62	-14	-7	-12	-30	-19	21
2: Δ Depth		-10	-6	-10	-22	-18	11
3: Δ Kyle's λ			66	76	69	-5	-1
4: Δ Amihud illq				50	49	-3	-6
5: Δ B/A spread					60	-1	-1
6: $\Delta\sigma$						41	-21
7: Δ trading vol							-27
8: Return							

Table VIII. Pairwise Correlations

This table shows the pairwise correlations (in %) using daily changes of the variables (except for the return which is computed as the daily change of log prices). The sample period is January 2009 – December 2022.

Exchange-Traded Liquidity

INTERNET APPENDIX

A.1. Internet Appendix: Additional Results and Robustness Checks

A.2. Internet Appendix: Proofs

A.3. Internet Appendix: CFTC Data

This section describes the trader types and their market position in the E-mini market. As per CFTC, the trader types in the futures markets consists of dealers, asset managers, leveraged hedge funds, ‘other reportable’ and non reportable. Dealers make up the supply side of the market. They seek to have matched books or offset their risk across markets and clients. Dealers of futures contracts consists of large banks (U.S. and non-U.S.) and dealers in securities, swaps and other derivatives. The demand side consists of asset managers, leveraged hedge funds and other reportable. Asset managers are institutional investors and include pension funds, endowments, insurance companies, mutual funds and portfolio managers whose clients are predominantly institutional. Leveraged hedge funds are typically hedge funds and other types of money managers, including registered commodity trading advisors (CTAs); registered commodity pool operators (CPOs) or unregistered funds identified by CFTC. Their strategies may involve taking outright positions or arbitrage within and across markets. The traders may be engaged in managing and conducting proprietary futures trading and trading on behalf of speculative clients. Reportable traders that are not placed into one of the first three categories are placed into the other reportables category. The traders in this category mostly are using markets to hedge business risk, whether that risk is related to foreign exchange, equities or interest rates. This category includes corporate treasuries, central banks, smaller banks, mortgage originators, credit unions and any other reportable traders not assigned to the other three categories.

As seen in figure A.2, asset managers make up the largest part of the market (when measured by open interest, i.e., the number of contracts outstanding) and are typically long in the market. Leveraged hedge funds are the second largest trader type on the demand side and they are typically short in the market. This can be due to speculation, but often it is for hedging purposes. The dealers are usually short in the market since they take the opposite side of trades. As seen in figure 3, the total number of registered dealer have remained constant throughout the sample period.

A.4. Internet Appendix: Traditional Measures of Liquidity

A. *Lee and Ready (1991) algorithm*

Many of the liquidity measures described below require signed transactions. The literature standard is to follow the Lee and Ready (1991) algorithm. In the Lee and Ready (1991) algorithm, a trade is classified as a buy if the trade price is above the midpoint of the best bid/offer (BBO) and as a sell if the trade price is below the midpoint of the BBO.

B. *Adverse selection measures*

- Kyle (1985) lambda: price impact; measured as the coefficient λ_{it} in

$$\text{ret}_{itn} = \delta_{it} + \lambda_{it} S_{itn} + \epsilon_{itn},$$

where, for the n th five-minute period on date t and security i , ret_{itn} is the security return and S_{itn} is the signed square-root dollar volume:

$$S_{itn} = \sum_{k \in n} \text{sign}(\$vol_{itnk}) \sqrt{|\$vol_{itnk}|}$$

- Five minute price impact: gross losses to liquidity demanders due to adverse selection (Glosten and Harris, 1988); calculated as:

$$\text{Price impact}_{it} = \frac{\sum_{k \in t} \$vol_{itk} q_{itk} (\log(M_{it,k+5}) - \log(M_{itk}))}{\sum_{k \in t} \$vol_{itk}},$$

where $q_{itk} = 1(-1)$ if the k th trade is a buy (sell), M_{itk} is the midpoint of the prevailing BBO at the time of the k th trade, and $M_{it,k+5}$ is the midpoint of the prevailing BBO five minutes after the k th trade

- Trade-related variance of changes in efficient price/cumulative impulse response: price moves associated with recent trades are private information-based; as in Hasbrouck (1991a,b) estimate a VAR for returns and order flow:

$$\begin{aligned} r_{it\tau} &= \sum_{k=1}^{10} \alpha_{itk} r_{it,\tau-k} + \sum_{k=1}^{10} \beta_{itk} q_{it,\tau-k} + \epsilon_{r,it,\tau} \\ q_{it\tau} &= \sum_{k=1}^{10} \gamma_{itk} r_{it,\tau-k} + \sum_{k=1}^{10} \phi_{itk} q_{it,\tau-k} + \epsilon_{q,it,\tau}, \end{aligned}$$

where $r_{it,\tau}$ is the log return based on the BBO midpoint for security i on date t from trade time $\tau - 1$ to trade time τ . Invert to get the VMA representation:

$$\begin{bmatrix} r_{it\tau} \\ q_{it\tau} \end{bmatrix} = \begin{bmatrix} a_{it}(L) & b_{it}(L) \\ c_{it}(L) & d_{it}(L) \end{bmatrix} \begin{bmatrix} \epsilon_{r,it,\tau} \\ \epsilon_{q,it,\tau} \end{bmatrix}$$

Then the variance of returns can be expressed as:

$$\sigma_{it,\omega}^2 = \underbrace{\left(\sum_{j=0}^{\infty} b_{it,j} \right)^2}_{\text{Trade-related}} \sigma_{it,q}^2 + \underbrace{\left(\sum_{j=0}^{\infty} a_{it,j} \right)^2}_{\text{Trade-orthogonal}} \sigma_{it,r}^2.$$

With this notation, we have:

- Trade-related component of variance of changes in the efficient price (Hasbrouck, 1991b):

$$R_{it,\omega} = \frac{\left(\sum_{j=0}^{\infty} b_{it,j}\right)^2 \sigma_{it,q}^2}{\sigma_{it,\omega}^2}$$

- Cumulative impulse response (Hasbrouck, 1991a):

$$IR_{it,\omega} = \sum_{j=0}^{\infty} b_{it,j}.$$

- Amihud illiquidity:

$$\text{Illiquidity}_{it} = 1000 \frac{|r_{it}|}{\$vol_{it}},$$

where $\$vol_{it}$ is the unsigned volume on day t .

- Easley, Kiefer, O'Hara, and Paperman (1996) probability of informed trade (PIN). Informed traders receive private signals with probability α . If signal is positive (probability δ), buy orders from informed and uninformed arrive with Poisson intensity $\mu + \epsilon_B$; sell orders arrive from uninformed traders only with intensity ϵ_S . If signal is negative, reverse is true and buy orders arrive with intensity ϵ_B , sell orders arrive with intensity $\mu + \epsilon_S$. The parameters α , μ , ϵ_B , ϵ_S are estimated via MLE, with the likelihood given by

$$L(D_{PIN,it}) = L_{NI}(D_{PIN,it}) + L_{I+}(D_{PIN,it}) + L_{I-}(D_{PIN,it}),$$

where $L_{NI}(D_{PIN,it})$ is the likelihood of observing B_{it} buys and S_{it} sells in a period without private information:

$$L_{NI}(D_{PIN,it}) = (1 - \alpha_i) e^{-\epsilon_{B_i}} \frac{\epsilon_{B_i}^{B_{it}}}{B_{it}!} e^{-\epsilon_{S_i}} \frac{\epsilon_{S_i}^{S_{it}}}{S_{it}!},$$

$L_{I+}(D_{PIN,it})$ is the likelihood of observing B_{it} buys and S_{it} sells in a period with a positive private signal:

$$L_{I+}(D_{PIN,it}) = \alpha_i \delta_i e^{-(\mu_i + \epsilon_{B_i})} \frac{(\mu_i + \epsilon_{B_i})^{B_{it}}}{B_{it}!} e^{-\epsilon_{S_i}} \frac{\epsilon_{S_i}^{S_{it}}}{S_{it}!},$$

and $L_{I-}(D_{PIN,it})$ is the likelihood of observing B_{it} buys and S_{it} sells in a period with a negative private signal:

$$L_{I-}(D_{PIN,it}) = \alpha_i (1 - \delta_i) e^{-\epsilon_{B_i}} \frac{\epsilon_{B_i}^{B_{it}}}{B_{it}!} e^{-(\mu_i + \epsilon_{S_i})} \frac{(\mu_i + \epsilon_{S_i})^{S_{it}}}{S_{it}!}.$$

The PIN of a security is then defined as the (conditional) probability of private information:

$$PIN_{it} \equiv \mathbb{P}(I_{it} = 1 | D_{PIN,it}) = \frac{L_{I+}(D_{PIN,it}) + L_{I-}(D_{PIN,it})}{L(D_{PIN,it})}.$$

- Odders-White and Ready (2008) PIN (OWR): extends Kyle (1985) to allow for days with no private information. The OWR model uses three variables: the day's full order imbalance y_{et} , the intraday return r_{dt} , and the overnight return r_{ot} . The model is identified through the assumption that the covariance matrix of these three variables differs between days with private information arrival and days with only public information. Let α_i be the probability that there is an information event on a given day, σ_{zi}^2 be the variance of the noise of the observed net order flow (y_{et}), σ_{ui}^2 be the variance of the net order flow from noise traders, σ_i^2 be the variance of the private signal received by the informed trader, $\sigma_{pd_i}^2$ be the variance of the intraday return, and $\sigma_{po_i}^2$ be the variance of the overnight return.

As with PIN, OWR is estimated via MLE, with the likelihood of observing $(y_{eit}, r_{dit}, r_{oit})$ on a day with and without an information event given by:

$$L_{I,it} = \alpha_i \phi(y_{eit}, r_{dit}, r_{oit}; \Omega_{I,i})$$

$$L_{NI,it} = \alpha_i \phi(y_{eit}, r_{dit}, r_{oit}; \Omega_{NI,i}).$$

Here, $\phi(\cdot; \Omega)$ is the joint normal pdf with mean 0 and covariance matrix Ω :

$$\Omega_{NI,i} = \begin{bmatrix} \sigma_{ui}^2 + \sigma_{zi}^2 & \sqrt{\alpha_i} \sigma_i \sigma_{ui} / 2 & -\sqrt{\alpha_i} \sigma_i \sigma_{ui} / 2 \\ \sqrt{\alpha_i} \sigma_i \sigma_{ui} / 2 & \sigma_{pd_i}^2 + \alpha_i \sigma_i^2 / 4 & -\alpha_i \sigma_i^2 / 4 \\ -\sqrt{\alpha_i} \sigma_i \sigma_{ui} / 2 & -\alpha_i \sigma_i^2 / 4 & \sigma_{po_i}^2 + \alpha_i \sigma_i^2 / 4 \end{bmatrix};$$

$$\Omega_{I,i} = \begin{bmatrix} (1 + \alpha_i^{-1}) \sigma_{ui}^2 + \sigma_{zi}^2 & \alpha_i^{-\frac{1}{2}} \sigma_i \sigma_{ui} / 2 + \sqrt{\alpha_i} \sigma_i \sigma_{ui} / 2 & \alpha_i^{-\frac{1}{2}} \sigma_i \sigma_{ui} / 2 - \sqrt{\alpha_i} \sigma_i \sigma_{ui} / 2 \\ \alpha_i^{-\frac{1}{2}} \sigma_i \sigma_{ui} / 2 + \sqrt{\alpha_i} \sigma_i \sigma_{ui} / 2 & \sigma_{pd_i}^2 + (1 + \alpha_i) \sigma_i^2 / 4 & (1 - \alpha_i) \sigma_i^2 / 4 \\ \alpha_i^{-\frac{1}{2}} \sigma_i \sigma_{ui} / 2 - \sqrt{\alpha_i} \sigma_i \sigma_{ui} / 2 & (1 - \alpha_i) \sigma_i^2 / 4 & \sigma_{po_i}^2 + (1 + \alpha_i) \sigma_i^2 / 4 \end{bmatrix}.$$

The probability of an information event occurring on date t is then:

$$OWN_{it} = \frac{L_{I,it}}{L_{I,it} + L_{NI,it}}.$$

C. Market power

- Realized spread: revenue to liquidity providers assuming that the liquidity provider can close their position at the midpoint prevailing 5 minutes after the trade:

$$rs_{it} = 2 \frac{\sum_{k \in t} \$vol_{itk} q_{itk} (\log(P_{itk}) - \log(M_{it,k+5}))}{\sum_{k \in t} \$vol_{itk}}.$$

D. Other measures

- Effective spread (Hasbrouck, 2010):

$$es_{it} = 2 \frac{\sum_{k \in t} \$vol_{itk} |\log(P_{itk}) - \log(M_{it,k+5})|}{\sum_{k \in t} \$vol_{itk}}.$$

- Bid-ask spread:

$$baspread_{it} = 2 \frac{ask_{it} - bid_{it}}{ask_{it} + bid_{it}},$$

where bid_{it} and ask_{it} are the prevailing bid and ask at the end of the period (e.g. at closing for intraday)

- Inverse limit order book slope (ILOBS) (Deuskar and Johnson, 2011): expected price impact; calculated as

$$ILOBS_{it\tau} = \frac{\sum_{k=1}^K (Mdist_{Ask,k,it\tau}^2 + Mdist_{Bid,k,it\tau}^2)}{\sum_{k=1}^K (Mdist_{Ask,k,it\tau} \$vol_{Ask,k,it\tau} - Mdist_{Bid,k,it\tau} \$vol_{Bid,k,it\tau})},$$

where $Mdist_{Ask,k,it\tau}$ is the absolute distance of the i limit order price on the ask side from the midprice and $Mdist_{Bid,k,it\tau}$ is the absolute distance of the i limit order price on the bid side from the midprice.

A.5. Internet Appendix: Figures

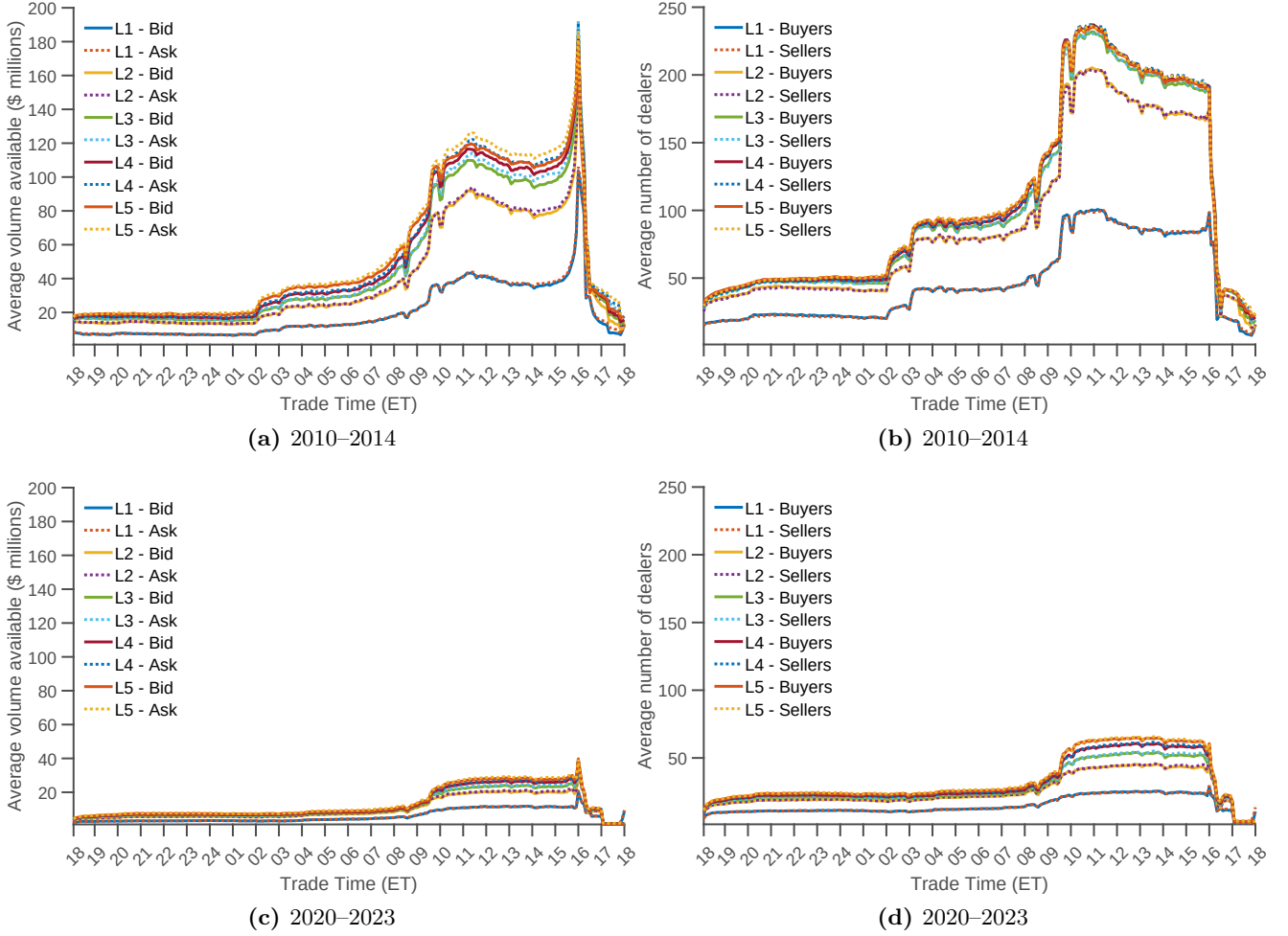


Figure A.1. Intraday liquidity and dealer number

Figure (a) and (c) plots the intraday average market depth measured as dollar volume available for level 1 to 5 of the order book for the S&P 500 E-mini futures contract. Figure (b) and (d) plots the intraday average number of dealers for level 1 to 5 of the order book. The dollar volume and dealer number are measured at a 5 minute frequency throughout the trading day. The sample period is January 2010 to December 2020 for (a) and (b) and April 2020 to December 2023 for (c) and (d).

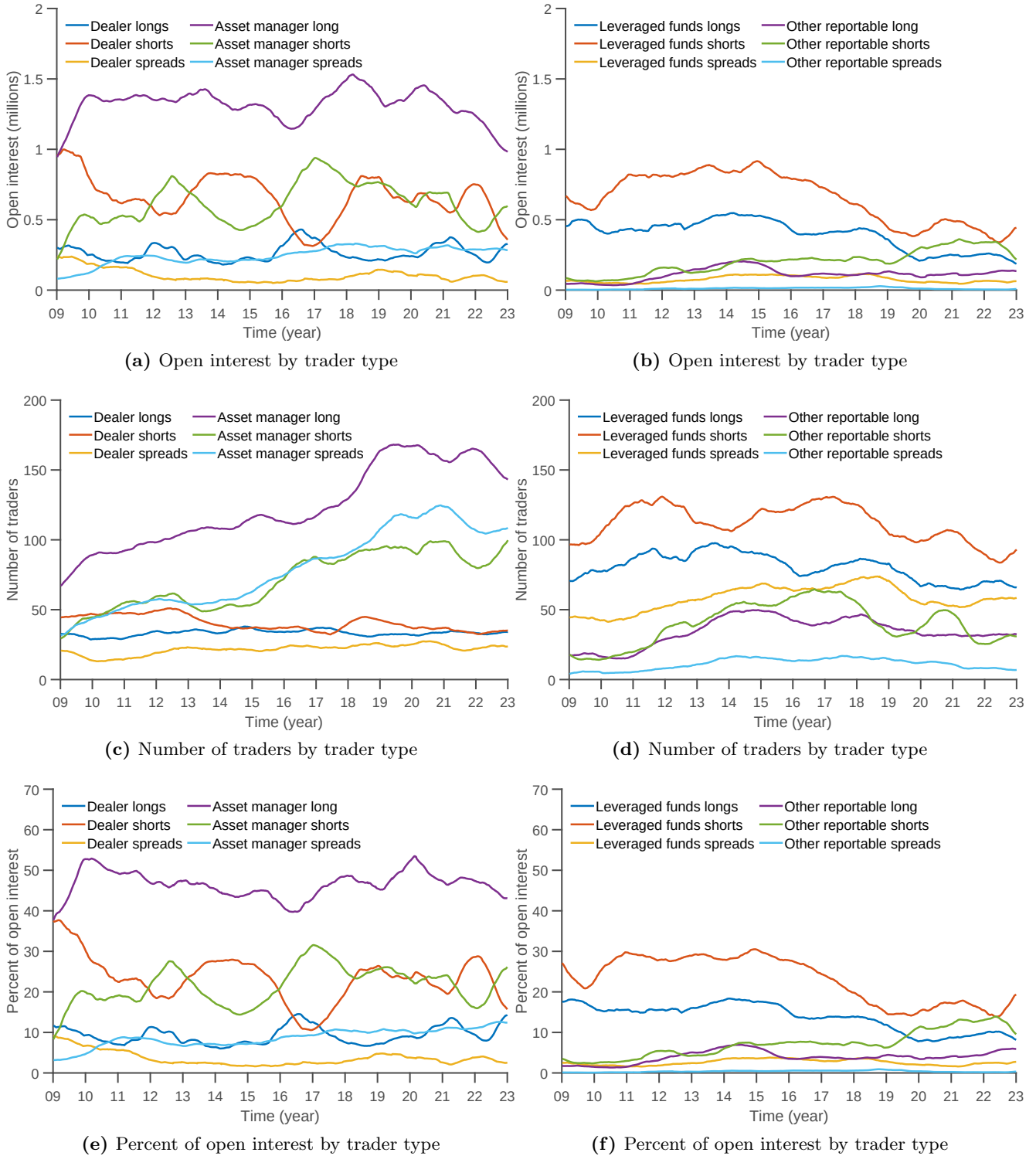


Figure A.2. Time series of open interest by trader type and number of traders
The figure plots the time series of the open interest and number of traders by type for the S&P 500 E-mini futures contract. The sample period is January 2009 to December 2022.

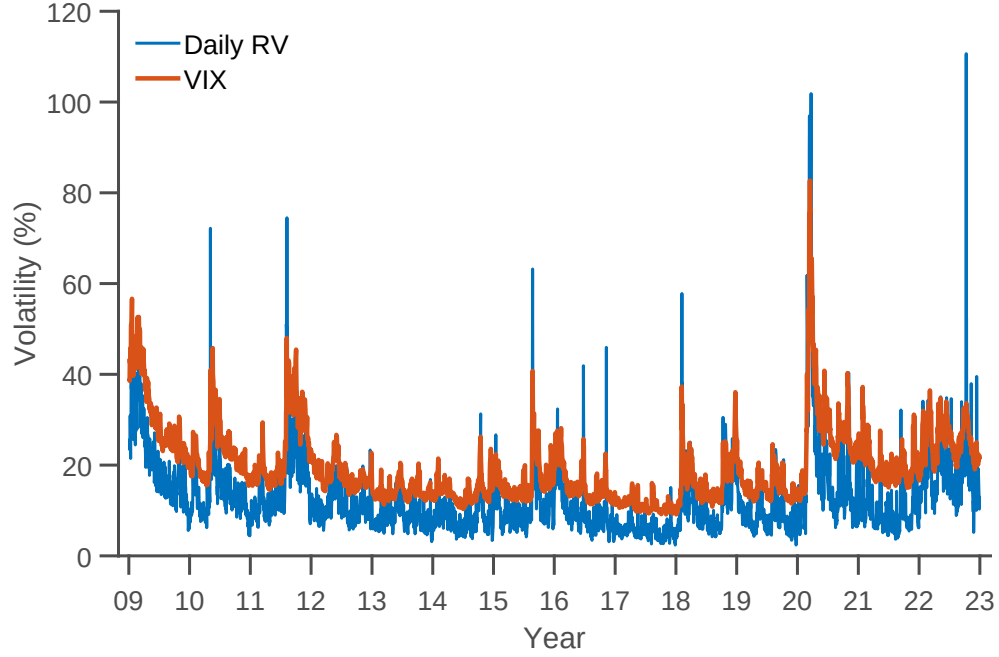


Figure A.3. Time series of realized volatility and VIX

The figure plots the time series of the daily VIX level and the daily realized volatility computed from quoted prices sampled at a 5-minute frequency. The sample period is January 2009 to December 2022.

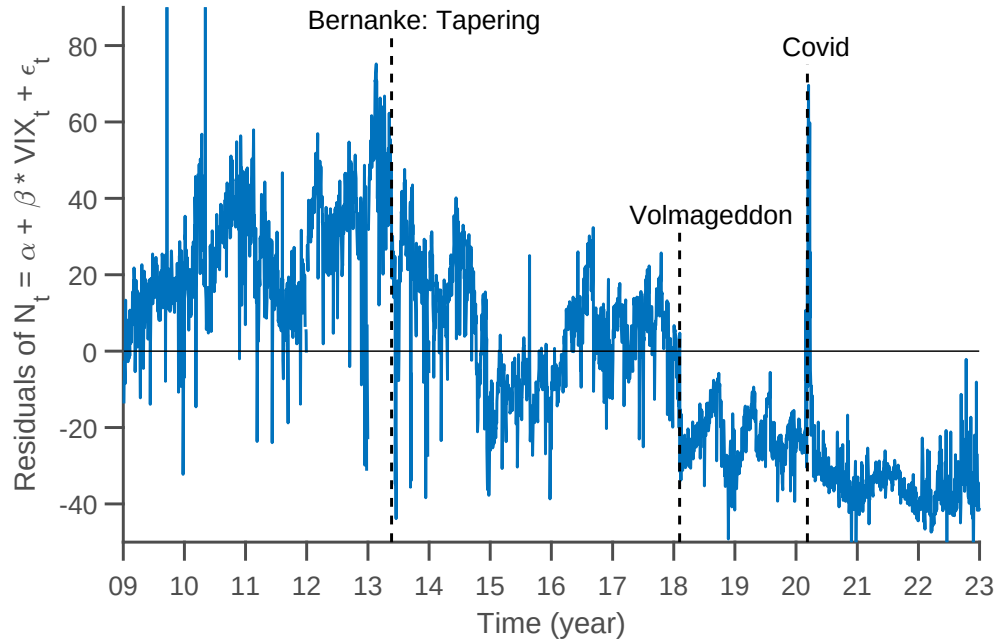


Figure A.4. Regression in levels – residuals

The figure plots the residuals of a linear regression in levels of the daily dealer number, N_t on the daily realized volatility and highlights the 3 distinct shocks to the liquidity level. The sample period is January 2009 to December 2022.

To handle the non-stationarity of the dealer number, we run separate regressions for each year in our sample period. Results are reported in figure A.5 and we see that the β -coefficients remain negative for all years, while the α and the predicted values, which measure the general of liquidity, are decreasing throughout the sample period, especially from 2018 onwards. The R^2 s are typically around 60%–70%, but significantly lower in 2013, 2017 and 2022. R^2_{2013} is low because of a few observations at the end of the year with very low liquidity compared the first part of the year (see figure 6 (a)). R^2_{2017} is low because all observations have approximately the same volatility and liquidity levels so the signal-to-noise ratio is low, and R^2_{2022} is low because liquidity was very low and not affected much by changes to volatility (see figure 6 (b)).

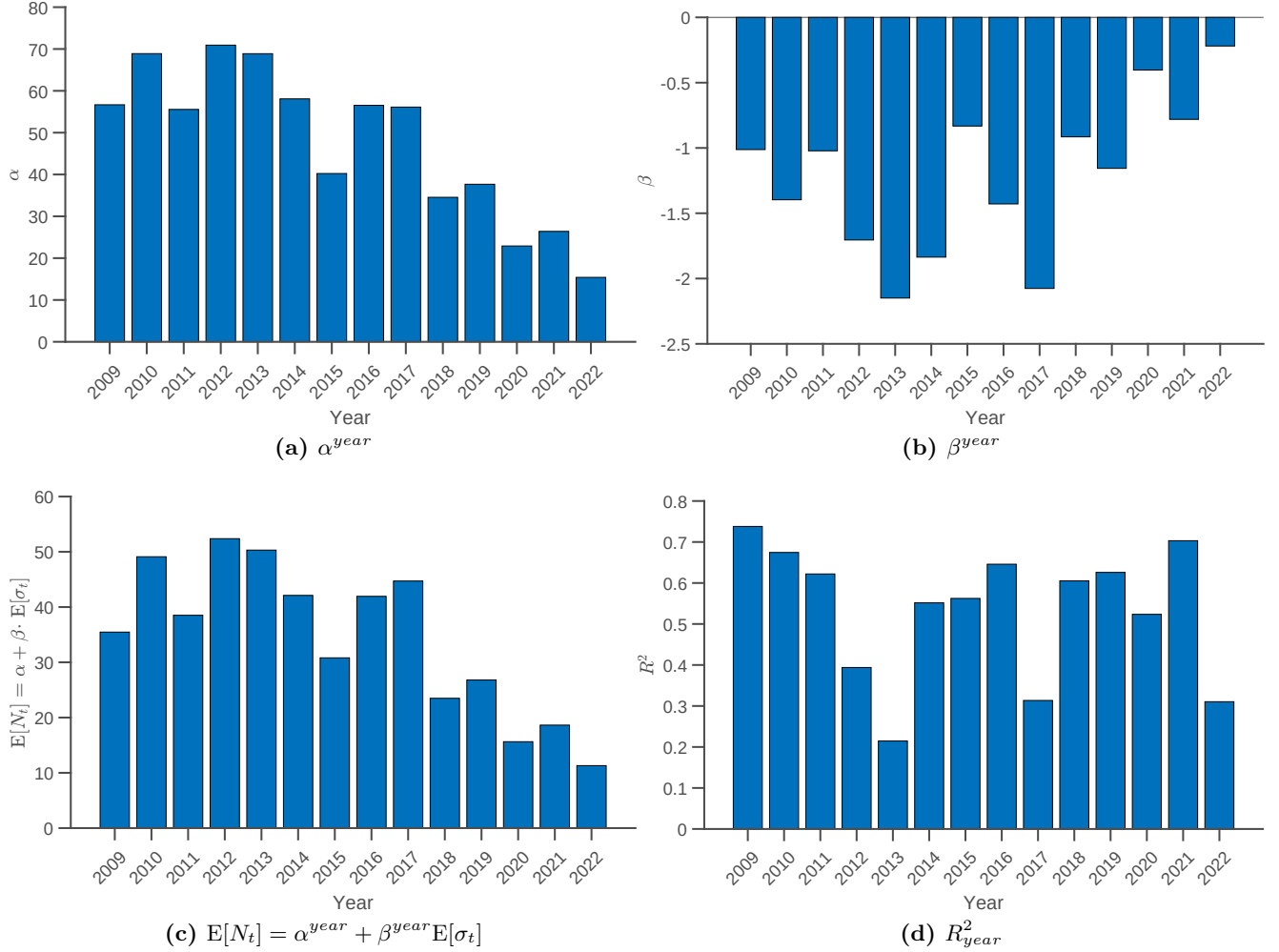


Figure A.5. Number of dealers regressed on volatility by year

The figure considers the contemporaneous relationship between the dealer number and volatility for the S&P 500 E-mini futures contract by fitting one regression per year. The dependent variable is liquidity on day t measured as the number of dealers, N_t , at level 1 of the LOB, and the explanatory variable is volatility on day t measured as realized volatility. The regression specification is $N_t = \alpha^{year} + \beta^{year} RV_t + \epsilon_t$ for all trading days t in a given year for $year = 2009, \dots, 2022$. Figure (a) shows the estimated α 's for each year, (b) shows the β -coefficients, (c) shows the predicted value of N for the average yearly volatility: $E[N_t] = \alpha^{year} + \beta^{year} E[\sigma_t]$, and (d) shows the coefficient of determination, R^2_{year} .

A.6. Internet Appendix: Tables

	(i)	(ii)	(iii)
$\Delta\sigma_t$	-0.53		-1.19
	[-0.66 -0.44]		[-1.32 -1.06]
$\Delta\sigma_t^2$		-0.31	0.93
		[-0.52 -0.23]	[0.78 1.17]
$R^2(\%)$	10.29	2.44	15.84

Table A.1. Liquidity-volatility relationship: bootstrapped

This table considers the contemporaneous relationship between liquidity and volatility for the S&P 500 E-mini futures contract. The dependent variable is the change in liquidity on day t which is measured as the change in the average daily number of dealers, N_t , at level 1 to 5 of the LOB. The explanatory variable(s) is changes to volatility (and/or variance) on day t measured using daily realized volatility computed from 5-minute log returns. The sample period is January 2009 to December 2022. The regression specifications are

$$\begin{aligned}
 (i) \quad & \Delta N_t = \alpha + \beta \Delta\sigma_t + \epsilon_t, \\
 (ii) \quad & \Delta N_t = \alpha + \beta \Delta\sigma_t^2 + \epsilon_t, \\
 (iii) \quad & \Delta N_t = \alpha + \beta_1 \Delta\sigma_t + \beta_2 \Delta\sigma_t^2 + \epsilon_t.
 \end{aligned}$$

95% confidence intervals are computed using the Fast Wild and bootstrap of Roodman, Nielsen, MacKinnon, and Webb (2019) originally developed for regression models with heteroskedasticity of unknown form and, like traditional bootstrap, the Wild bootstrap is robust to large-sample assumptions.

	(i)	(ii)	(iii)
$\Delta\sigma_t$	-0.53 (-6.27)		-1.19 (-9.72)
$\Delta\sigma^2_t$		-0.31 (-3.16)	0.93 (6.15)
α	0.08 (0.58)	0.11 (0.83)	0.05 (0.38)
$R^2(\%)$	10.30	2.45	15.85

Table A.2. Liquidity-volatility relationship: fixed effects

This table considers the contemporaneous relationship between liquidity and volatility for the S&P 500 E-mini futures contract. The dependent variable is the change in liquidity on day t which is measured as the change in the average daily number of dealers, N_t , at level 1 to 5 of the LOB. The explanatory variable(s) is changes to volatility (and/or variance) on day t measured using daily realized volatility computed from 5-minute log returns. The sample period is January 2009 to December 2022. The regression specifications are

$$\begin{aligned}
(i) \quad \Delta N_t &= \alpha + \alpha^Y + \beta \Delta\sigma_t + \epsilon_t, \\
(ii) \quad \Delta N_t &= \alpha + \alpha^Y + \beta \Delta\sigma_t^2 + \epsilon_t, \\
(iii) \quad \Delta N_t &= \alpha + \alpha^Y + \beta_1 \Delta\sigma_t + \beta_2 \Delta\sigma_t^2 + \epsilon_t,
\end{aligned}$$

where α^Y is a year fixed effect (year dummy) which is estimated but not reported. t -statistics are computed with a Newey and West (1987) correction with 45 lags. The sample period is January 2009 – December 2022.

	(i)	(ii)
$\Delta\sigma_{t-1}$	0.00 (4.07)	0.00 (5.53)
$\Delta\sigma_{t-1}^2$		-0.00 (-3.08)
α	-0.00 (-0.75)	-0.00 (-0.75)
$R^2(\%)$	0.98	1.51

Table A.3. Predicting margin changes

This table shows that changes in volatility on day $t - 1$ predict changes in margins on day t and for the S&P 500 E-mini futures contract. The dependent variable is the change in margin percentage on day t measured the USD margin requirement in percent of the E-mini contract value, and the predictor variable is the change in volatility from day $t - 2$ to $t - 1$ measured using daily realized volatility computed from 5-minute log returns. The sample period is January 2009 to December 2022. The regression specifications are

$$\begin{aligned}
(i) \quad & \Delta\kappa_t = \alpha + \beta\Delta\sigma_{t-1} + \epsilon_t, \\
(ii) \quad & \Delta\kappa_t = \alpha + \beta_1\Delta\sigma_{t-1} + \beta_2\Delta\sigma_{t-1}^2 + \epsilon_t,
\end{aligned}$$

t -statistics are computed with a Newey and West (1987) correction with 45 lags. The sample period is January 2009 – December 2022.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
ΔN_{t-1}	-0.23 [-0.29 -0.17]	-0.21 [-0.27 -0.15]	-0.24 [-0.30 -0.18]	-0.23 [-0.29 -0.17]	-0.21 [-0.27 -0.15]	-0.25 [-0.31 -0.19]
ΔVIX_{t-1}	-0.61 [-0.77 -0.47]		-1.41 [-1.78 -1.10]			
ΔVIX_{t-1}^2		-0.52 [-0.97 -0.33]	1.17 [0.90 1.95]			
ΔRV_{t-1}				-0.16 [-0.25 -0.09]		-0.32 [-0.43 -0.20]
ΔRV_{t-1}^2					-0.11 [-0.25 -0.01]	0.21 [0.02 0.37]
$R^2(\%)$	6.07	4.90	6.83	4.99	4.43	5.24

Table A.4. Predicting Liquidity: bootstrapped

This table considers the relationship between changes in liquidity on day t and changes in volatility on day $t-1$ for the S&P 500 E-mini futures contract. The dependent variable is the liquidity change on day t measured as the change in number of dealers, $\Delta N_t = N_t - N_{t-1}$, at level 1 of the LOB, and the predictor variable is the change in volatility from day $t-2$ to $t-1$ measured with either the VIX or realized volatility. The sample period is January 2009 to December 2022. The regression specifications are

- (i) $\Delta N_t = \alpha + \beta \Delta VIX_{t-1} + \epsilon_t$,
- (ii) $\Delta N_t = \alpha + \beta \Delta VIX_{t-1}^2 + \epsilon_t$,
- (iii) $\Delta N_t = \alpha + \beta_1 \Delta VIX_{t-1} + \beta_2 \Delta VIX_{t-1}^2 + \epsilon_t$,
- (iv) $\Delta N_t = \alpha + \beta \Delta RV_{t-1} + \epsilon_t$,
- (v) $\Delta N_t = \alpha + \beta \Delta RV_{t-1}^2 + \epsilon_t$,
- (vi) $\Delta N_t = \alpha + \beta_1 \Delta RV_{t-1} + \beta_2 \Delta RV_{t-1}^2 + \epsilon_t$.

95% confidence intervals are computed using the Fast Wild and bootstrap of Roodman, Nielsen, MacKinnon, and Webb (2019) originally developed for regression models with heteroskedasticity of unknown form and, like traditional bootstrap, the Wild bootstrap is robust to large-sample assumptions.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
ΔN_{t-1}	-0.23 (-9.09)	-0.21 (-8.48)	-0.24 (-9.63)	-0.23 (-8.90)	-0.21 (-8.47)	-0.25 (-9.09)
ΔVIX_{t-1}	-0.61 (-5.29)		-1.40 (-6.87)			
ΔVIX_{t-1}^2		-0.52 (-2.23)	1.17 (4.49)			
ΔRV_{t-1}				-0.16 (-3.85)		-0.31 (-5.28)
ΔRV_{t-1}^2					-0.11 (-1.90)	0.21 (2.73)
α	0.08 (0.53)	0.10 (0.68)	0.07 (0.48)	0.12 (0.76)	0.12 (0.80)	0.11 (0.73)
$R^2(\%)$	6.09	4.91	6.84	5.00	4.45	5.26

Table A.5. Predicting Liquidity: fixed effects

This table considers the relationship between changes in liquidity on day t and changes in volatility on day $t-1$ for the S&P 500 E-mini futures contract. The dependent variable is the liquidity change on day t measured as the change in number of dealers, $\Delta N_t = N_t - N_{t-1}$, at level 1 of the LOB, and the predictor variable is the change in volatility from day $t-2$ to $t-1$ measured with either the VIX or realized volatility. The sample period is January 2009 to December 2022. The regression specifications are

$$\begin{aligned}
(i) \quad \Delta N_t &= \alpha + \alpha^Y + \beta \Delta VIX_{t-1} + \epsilon_t, \\
(ii) \quad \Delta N_t &= \alpha + \alpha^Y + \beta \Delta VIX_{t-1}^2 + \epsilon_t, \\
(iii) \quad \Delta N_t &= \alpha + \alpha^Y + \beta_1 \Delta VIX_{t-1} + \beta_2 \Delta VIX_{t-1}^2 + \epsilon_t, \\
(iv) \quad \Delta N_t &= \alpha + \alpha^Y + \beta \Delta RV_{t-1} + \epsilon_t, \\
(v) \quad \Delta N_t &= \alpha + \alpha^Y + \beta \Delta RV_{t-1}^2 + \epsilon_t, \\
(vi) \quad \Delta N_t &= \alpha + \alpha^Y + \beta_1 \Delta RV_{t-1} + \beta_2 \Delta RV_{t-1}^2 + \epsilon_t.
\end{aligned}$$

where α^Y is a year fixed effect (year dummy) which is estimated but not reported. t -statistics are computed with a Newey and West (1987) correction with 45 lags. The sample period is January 2009 – December 2022.