High-Frequency Arbitrage and Market Illiquidity

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Abstract

During times of market stress, asset prices often deviate from their fundamental values due to pervasive market frictions that impede the timely deployment of arbitrage capital. This leads to transitory volatility, a latent factor that can destabilize markets and cause systemic risk. In this paper, I introduce a novel, real-time measure of market-wide illiquidity based on the transitory volatility of the SPY ETF, which tracks the S&P500. Despite being derived from an index, this measure captures commonality in stock-level illiquidity. Moreover, the measure can be computed intra-daily and generates an annual premium of 8.76%, which cannot be explained by existing risk factors, including traditional illiquidity proxies. The methodology is further extended to the Treasury market by proposing a new funding illiquidity measure, allowing for the exploration of liquidity dynamics across markets.

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1 Introduction

Market liquidity is essential for a proper functioning economy, as it contributes to the efficiency of financial markets, allowing them to perform as designed. During normal times, there is ample liquidity, and arbitrageurs help keep asset prices aligned with their fundamental values. However, during times of market stress, pervasive market frictions impede the swift deployment of arbitrage capital, resulting in a scarcity of liquidity. As a result, the law of one price breaks down and assets trade away from fundamentals. If arbitrage capital were easily accessible, arbitrageurs would be able to correct excessive price fluctuations created by deviations from fundamental values.[1] However, during turbulent periods, the inability to swiftly deploy arbitrage capital results in excess volatility, driven by non-fundamental factors. This manifests as transitory fluctuations in asset prices over short time frames. Such volatility not only highlights challenges in the market-making process, but also has the potential to destabilize securities markets and create systemic risk. Consequently, transitory volatility has long been a concern for regulators, and I argue that it is of first-order importance in capturing market illiquidity.[2]

I make the following key contributions to the literature. First, I propose a new market-wide illiquidity measure based on the transitory volatility of the SPY ETF, which tracks the S&P500. This is a latent factor that captures deviations between transaction prices and fundamental values, and reflects the slow movement of arbitrage capital during times of market stress.[3] I derive the measure theoretically by combining continuous-time econometrics, market microstructure theory, and no-arbitrage arguments, and I compute it in trade time. I validate the measure by showing that it correlates with market-wide illiquidity events, standard measures of economic uncertainty, and existing illiquidity proxies. Despite these correlations, my measure provides unique insights, captures commonality in stock-level illiquidity, both theoretically and empirically, and can be computed in real-time.

Second, I show that this illiquidity measure is a priced risk factor. Sorting stocks based on their historical exposure to the measure reveals a significant spread in post-formation abnormal returns, which cannot be explained by classical risk factors, including existing illiquidity proxies. The economic intuition is that during periods of market stress, participants are capital constrained, and arbitrage capital is slow-moving, making illiquidity a systematic source of risk. Moreover, I demonstrate that this illiquidity factor is not subsumed by existing risk factors, further confirming

[1] See, e.g., Shleifer and Vishny (1997).

[2] See Order Approving, on a Pilot Basis, the National Market System Plan to Address Extraordinary Market Volatility by BATS Exchange, Inc., BATS Y-Exchange, Inc., Chicago Board Options Exchange, Incorporated, Chicago Stock Exchange, Inc., EDGA Exchange, Inc., EDGX Exchange, Inc., Financial Industry Regulatory Authority, Inc., NASDAQ OMX BX, Inc., NASDAQ OMX PHLX LLC, The Nasdaq Stock Market LLC, National Stock Exchange, Inc., New York Stock Exchange LLC, NYSE MKT LLC, and NYSE Arca, Inc. ("Approval Order"), Release No. 34-67091 (May 31, 2012), 77 FR 33498 (June 6, 2012) (File No. 4-631).

[3] Fundamental values would prevail in a frictionless market.

its novelty.

Third, I extend the methodology to the Treasury market by developing a real-time funding illiquidity measure based on the SHV ETF, which tracks the ICE Short US Treasury Securities Index. This extension allows for an exploration of liquidity dynamics across asset classes. I find that, consistent with theory, illiquidity in the stock market and in bonds reinforces each other, as does the relationship between bond illiquidity and market volatility.[4]

Liquidity plays a crucial role in the economy by facilitating interactions between buyers and sellers and fostering capital formation.[5] The overall improvement in liquidity over the past two decades can be partly attributed to structural changes in the markets, which have significantly reduced trading costs, such as commissions, bid-ask spreads, and price impacts.[6]

Key innovations in market structure include the growth of alternative trading systems, which offer additional liquidity channels and have intensified competition among legacy exchanges, driving them to innovate. Other changes such as the transition to decimalization in the trading process, the rise of electronic trading systems, and the advent of financial innovations powered by new technologies (e.g., automated algorithmic trading, online brokerage accounts, and inter-market linkages) have transformed access to stock trading . However, events like the Flash Crash of May 6, 2010, have brought to light the vulnerability of liquid, automated markets to severe price dislocations.[7]

The Flash Crash demonstrated that a quick erosion in market liquidity could lead to a sharp increase in transitory market volatility, prompting regulators to introduce mechanisms in U.S. equity markets aimed at curbing "extraordinary transitory volatility".[8]

Building on these observations, I focus on the relationship between illiquidity and transitory price volatility. While net asset values (NAVs) are commonly used to proxy for fundamentals, they are calculated using transaction prices, which include liquidity effects. In my quest to isolate the illiquid component in prices, I focus on deviations of transaction prices from latent fundamental values, rather than from NAVs.

To study market-wide illiquidity, I concentrate on the transitory volatility of SPY. As a proxy for the market portfolio at high-frequency, SPY is a useful instrument here. SPY can be redeemed for, or created in exchange for the underlying basket of securities held by the S&P500 index. As a result, arbitrage forces help keep SPY prices in line with fundamentals. Any deviations

[4] The model in Brunnermeier and Pedersen (2009) posits that market liquidity and funding liquidity reinforce each other, while the model in Gromb and Vayanos (2002) predicts that higher volatility tightens funding liquidity.

[5] It is difficult for firms to raise funds in a capital constrained economy (see, e.g. Holmstrom and Tirole, 2001).

[6] See, e.g. Chordia, Roll and Subrahmanyam (2011), and Hendershott, Jones, and Menkveld (2011).

[7] See the Report of the Staffs of the CFTC and SEC to the Joint Advisory Committee on Emerging Regulatory Issues at https://www.sec.gov/news/studies/2010/marketevents-report.pdf.

[8] See Release No. 34-85623 (April 11, 2019), Order Approving the National Market System Plan to Address Extraordinary Market Volatility, available at https://www.sec.gov/rules/sro/nms.htm.

from fundamental values stem from pervasive market frictions that hinder the timely execution of arbitrage, signaling market-wide illiquidity events. These deviations reflect strains on the market-making infrastructure, which slow the movement of arbitrage capital. Such frictions—like funding constraints in intermediary-based asset pricing—signal periods when it is costly to enter or exit the market portfolio.[9]

The Mini Flash Crash of August 24, 2015, provides a more recent example of how slow-moving arbitrage capital can affect the valuation of exchange-traded products (ETPs). During the morning hours of that day, market disruptions occurred as circuit breakers got triggered by illiquidity. Large order imbalances arose due to heavy selling pressure, as investors reacted to overnight global macro concerns.

ETPs depend on the market makers to arbitrage away any discrepancies between their share price and the value of the underlying portfolio. However, uncertainty surrounding hedging strategies that morning led market makers to temporarily cease arbitraging ETPs. Figure 1 displays the price behavior of an ETP and its underlying index during the Mini Flash Crash. The plot illustrates the price dislocation in the ETP, caused by market makers refraining from committing capital to provide liquidity, and highlights the presence of excess, or transitory, volatility in the ETP on that day.[10]

To measure SPY's transitory volatility, I rely on high-frequency data, assuming that transaction prices contain two latent components: a fundamental (or permanent) component and a market microstructure friction (or transitory) component. The permanent component reflects the incorporation of new information into asset prices through the price discovery process. The transitory component, however, may be attributable to the demands of impatient, uninformed traders or to the inventory risk exposure of financial intermediaries. This component captures the frictions in the market and is closely tied to illiquidity.

While these two components capture different economic phenomena, both tend to experience higher volatility during periods of economic distress. The volatility of the fundamental component increases with economic uncertainty, while the transitory volatility rises due to the scarcity and sluggish deployment of arbitrage capital, leading to market illiquidity. Therefore, it is essential to distinguish between these two sources of volatility.

High-frequency transaction data are crucial for this analysis because they offer valuable insights into market frictions, particularly through the transitory price component (see, e.g., Stoll, 2000). To estimate transitory volatility, I use millisecond-timestamped trade-level data from February 1, 2001, to December 31, 2019. I provide economic support for this measure by documenting that it

[9] See, e.g., Huang and Wang (2009), and Vayanos and Wang (2012) for models incorporating the effect of frictions on illiquidity.

[10] See more details in the BlackRock Report on the August 24 Flash Crash available at https://www.sec.gov/comments/265-29/26529-52.pdf

increases during periods of heightened political uncertainty, when market makers may face adverse selection and scale back their liquidity provision. Also, to address a possible concern that the proposed measure may be primarily driven by SPY's idiosyncratic events, I show that it captures commonality in stock-level illiquidity.

Additionally, as O'Hara (2003) suggests, just as price discovery influences traders' risks, liquidity effects also impact traders' returns, thereby affecting utility and asset prices. To evaluate the pricing ability of the proposed illiquidity measure, I sort stocks into portfolios based on their exposure to (innovations in) this factor. I find that stocks in the first decile (with the most negative illiquidity beta) exhibit higher average returns compared to stocks in the tenth decile (with the most positive illiquidity beta). Consequently, I construct a traded illiquidity factor using a long-short portfolio, holding decile 1 and shorting decile 10, and show that this portfolio generates an average annual return of 8.76% over the period from January 2003 to December 2019.[11]

One possible explanation for the negative relationship between illiquidity exposure and average returns lies in how assets behave during times of crisis. Illiquidity is the outcome of aggregate trading frictions, which tend to be more severe in bad states of the world. Assets whose returns are positively correlated with (changes in) illiquidity (such as stocks in decile 10) provide a hedge during these times, thereby requiring relatively lower expected returns. In contrast, assets whose returns are negatively correlated with (changes in) illiquidity (like stocks in decile 1) are perceived as relatively riskier, and investors require a premium for holding them.

To further validate the measure as a risk factor, I demonstrate that it is not redundant by showing that it is not spanned by classical risk factors, including existing illiquidity measures.

Lastly, I extend the methodology used to construct the market illiquidity measure to other asset classes.[12] Specifically, I develop a market-wide illiquidity proxy in the Treasury bond market, using the same approach and the SHV ETF.[13] I find that this bond illiquidity measure aligns closely with existing funding liquidity metrics in capturing commonality in bond-level illiquidity. Furthermore, I investigate the inter-market liquidity dynamics and show that market illiquidity and bond illiquidity mutually reinforce each other, as do bond illiquidity and market volatility.

1.1 *Related Literature*

This paper draws on various strands of literature. On the theoretical side, the distinction between permanent and transitory price components is rooted in the work of Stoll (1978), Ho and Stoll (1983), and Grossman and Miller (1988), where market makers facing inventory risk charge a price

[11] This specific exercise uses the first 2 years of data for portfolio formation, which leads to a shorter sample period for building the traded market illiquidity measure, when compared to the raw market illiquidity measure.

[12] I am grateful to Joel Hasbrouck for suggesting this extension.

[13] The SHV ETF tracks an index composed of U.S. Treasury bonds with remaining maturities of one year or less, the ICE Short US Treasury Securities Index.

for temporarily holding a position that differs from the fundamental price. Glosten and Milgrom (1985) extend this by introducing adverse selection, where specialists (market makers) trade with informed customers and as result, charge a bid-ask spread that reflects the gap between observed and realizable returns. In the Kyle (1985) model, informed traders exploit transitory price errors while aligning their trades with permanent price shifts. Hasbrouck (1993) emphasizes how transient inventory control effects (as well as other noninformation imperfections) influence security prices, alongside the incorporation of permanent information. Brunnermeier and Pedersen (2009) define market liquidity as the difference between the transaction price and the fundamental value. Lastly, Sadka (2005) explores the pricing of both the fixed and variable components of liquidity risk.

This paper adds to the empirical literature that identifies liquidity using "noise" or "price pressure" measures. Hasbrouck (1993) examines the variance of the stock-level pricing error as a measure of market quality. Bandi and Russell (2006), along with Ait-Sahalia and Yu (2009), link microstructure noise at the stock level to illiquidity, while Zhang, Li, and Bollerslev (2022) treat microstructure noise volatility as a proxy for illiquidity. Hu, Pan, and Wang (2013) introduce a measure of market-wide illiquidity based on the average price deviations from fundamentals in the Treasury market. In more recent work, Hendershott and Menkveld (2014) investigate deviations from the efficient price, or "price pressures," on the NYSE, which arise when risk-averse intermediaries provide liquidity to investors arriving asynchronously. My approach differs from these studies by constructing a market-wide illiquidity measure that captures the slow movement of arbitrage capital, which is particularly prominent during times of market stress.

This paper also adds to the extensive body of research on various dimensions of liquidity, particularly its systematic pricing. Notable works by Huberman and Halka (2001), Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), Bekaert, Harvey and Lundblad (2007), Korajczyk and Sadka (2008), Sadka (2009), among others, have examined liquidity pricing (see, e.g., the excellent surveys on market liquidity by Amihud, Mendelson, and Pedersen, 2005; Vayanos and Wang 2012b, 2013). Existing literature has proposed various market illiquidity measures, which aggregate security-level illiquidity, with most relying on transaction volume data. In contrast, this paper introduces a market-wide illiquidity proxy computed at the aggregate level, making it independent of firm-level data, while still capturing the commonality in stock-level illiquidity. Furthermore, leveraging the high-frequency transaction data available for SPY (now reported to tape with nanosecond timestamps), this measure offers a real-time assessment of illiquidity that can be computed at much higher frequencies than traditional measures, such as over short intraday intervals.

Finally, this paper adds to the literature on asset price dynamics with slow-moving intermediation capital. Mitchell, Pedersen, and Pulvino (2007) explore scenarios where real world frictions impede arbitrage capital, causing significant and persistent price deviations from fundamental val-

ues. Duffie (2010) emphasizes that impediments to capital formation lead to temporary asset price distortions that eventually correct. Even in highly active markets, such as those utilizing electronic limit-order books, high-frequency data reveals that price dynamics still reflect the slow movement of capital.[14] For instance, Biais, Hillion, and Spatt (1995) examine data from the Paris Bourse (later Euronext) and establish a connection between the bid-ask spread and the speed at which limit orders supplying liquidity arrive.[15] This paper builds on that literature by documenting the relationship between slow-moving capital and market illiquidity.

The remainder of the paper is structured as follows. Section 2 describes the data and the methodology used for identifying the new market illiquidity measure. Section 3 provides empirical support for the proposed measure. Section 4 evaluates its pricing ability. Section 5 extends the methodology to the Treasury market. Section 6 concludes. The Online Appendix presents details on ETFs.

2 Identifying the New Market Illiquidity Measure

2.1 *High-Frequency Arbitrage*

As mentioned above, in what follows I use SPY to proxy for the market portfolio. SPY is an ETF that represents ownership of a trust invested in the S&P500 index. SPY generally corresponds, before expenses, to the price and yield performance of the S&P500 Index.[16] SPY trades like a stock at approximately one-tenth of the level of the S&P500 index. It is highly liquid, and there are plenty of buyers willing to enter into a long position, this way ensuring that the price will rarely be driven to unjustifiably low levels. Also, SPY relies on market makers to keep it aligned with its NAV. This is achieved via the creation/redemption feature of SPY. For instance, market makers will buy SPY shares if SPY trades at a discount, and redeem them in exchange for shares in the underlying basket of securities. And they will buy shares in the S&P500 if SPY trades at a premium, and exchange them for newly issued SPY shares. While this exchange takes place at the end of the trading day, SPY's values will not deviate much from its NAV during the day either, because the future convergence of prices would open up the possibility for simple, immediate investment opportunities and the authorized participants (APs) will lock in intraday profits.[17] [18] Therefore,

[14] See Darrell Duffie, *"Presidential Address: Asset Price Dynamics with Slow-Moving Capital"* (2010).

[15] Further relevant theories on competition, price impacts and price reversals can be found in Goettler, Parlour, and Rajan (2005, 2009), and Rosu (2009).

[16] I find a significant (at the 1% level) correlation of 99.55% between the intra-daily (open-to-close) returns of SPY and the value-weighted returns of the S&P500 (excluding dividends) over the period February 2001 - December 2019.

[17] As Elton et al. (2002) point out, the process of share deletion/creation acts as an extremely effective mechanism in keeping prices close to NAV and assuring that potential differences disappear quickly.

[18] See Hill, Nadig and Hougan (2015) for more details on ETFs. See Cherkes, Sagi and Stanton (2006) for further discussions and comparisons between ETFs and closed-end funds.

SPY trades with negligible premiums or discounts in liquid markets, as arbitrage forces keep it in line with the NAV. Any deviations of SPY transaction prices from fundamental values represent unexploited profits, and reflect liquidity constraints faced by slow moving arbitrage capital. Lower market liquidity may thus be expected to lead to larger deviations (see more details on ETFs in the Online Appendix).[19]

More generally, it is well-known from market microstructure theory that transaction prices (and, as said, NAVs are computed at transaction values) differ from fundamental values.[20] The size of these deviations will, again, depend on liquidity. Aggregate liquidity will affect both the size of the deviations between SPY's prices and NAVs (given the previous arbitrage arguments), and the size of the deviations between the transaction prices of the underlying basket of securities (which determine the NAVs) and the latent fundamental values. Lower aggregate liquidity may be expected to lead to larger overall deviations.

For example, during the Flash Crash event of August 24, 2015, equity markets were under stressed conditions in the morning hours, due to disruptions in trading. More precisely, trading in some of the constituents of the S&P500 got paused as stock-level circuit breakers got triggered in the market. As a result, the high-frequency arbitrage mechanism detailed above was disrupted that morning because market makers could not assess the NAV, and were thus unable to build their hedging position in ETPs like SPY. As a result, they did not commit capital to provide liquidity in the market, and ETPs ended up trading away from their fundamental values.

Finally, it should be noticed that, although NAVs have been widely used to proxy for fundamentals, they are stale.[21] More importantly, NAVs include liquidity because they are computed at transaction prices. In light of these arguments, and because I want to isolate the illiquidity component in prices, rather than focusing on deviations of transaction prices from NAVs (or IOPVs, or IIVs), I focus on the deviations of transaction prices from latent fundamental values.

[19] Market liquidity and funding liquidity re-enforce each other (see, e.g., Gromb and Vayanos (2002) and Brunnermeier and Pederson (2009)) and therefore, funding illiquidity may also have an indirect effect on price deviations. However, I leave the analysis of the empirical relation between funding liquidity and market liquidity to future work.

[20] The NAV is evaluated at the closing transaction price of each of the assets. Each closing transaction price could be higher or lower than the individual fundamental value, and the closing transaction could occur earlier in the day, especially for less frequently-traded stocks.

[21] While the NAV is computed at market close, there is an intraday value calculated by an exchange and distributed through quote services every 15 seconds, called the Indicative Optimized Portfolio Value (IOPV) or Intraday Indicative Value (IIV). However, in the context of this study, where the data are handled with a second timestamp frequency, the IIV(IOPV) intra-day values are stale.

2.2 *SPY Data*

Today, SPY is the largest and most liquid ETF.[22] However, this was not always the case. Figure 1 of the Online Appendix presents the daily SPY dollar and share trading volume series since its inception, based on data downloaded from the CRSP database in wrds. The plots suggest that trading in SPY has picked up around years 2000-2001. Because I need a fairly liquid factor to capture illiquidity events, I discard the earlier data. Furthermore, decimalization got completed during the 2000-2001 period, and the most recent change in tick size has been shown to have a substantial effect on the entire trading process, affecting liquidity in the market (see, e.g., Bessembinder, 2003). SPY is a NYSE Arca - listed security, and the last day of \$1/16 tick-size trading was January 28, 2001 for NYSE - and NYSE American (former AMEX) - listed securities.[23] Therefore, to cover only one liquidity regime, I start my sample on February 2001, when decimalization got completed for SPY. The sample ends on December 2019.

I download the ultra-high frequency SPY transaction price data from the Trade and Quote (TAQ) database in wrds. I use the Monthly TAQ database for the period January 2001-December 2014 (Monthly TAQ data end in 2014). Over this period, TAQ reports data for the Consolidated Tape System with a second timestamp. I then append to the sample the data collected from the Daily TAQ database, where trades are reported to the tape with a millisecond timestamp for the period January 1, 2015-July 26, 2015, with a microsecond timestamp for the period July 27, 2015-September 17, 2017, and with a nanosecond timestamp after September 17, 2017. Because the construction of the illiquidity measure here relies on applying asymptotic results to ultra-high frequency data, I make sure to have a consistent frequency throughout the sample. To this end, I follow the methodology used by wrds in the Monthly TAQ database, and I truncate the millisecond, microsecond, and nanosecond timestamps and I "floor" them to a second level for the period 2015-2019. I end up with second-level timestamp transaction data for the period February 1, 2001-December 31, 2019.

The transaction data come from the primary exchanges that have traded SPY over the time period under consideration, namely NASDAQ, NYSE ARCA, BATS and FINRA ADF. I consider only valid transactions, where the trading volume is positive, the trade correction indicator takes the values 0, 1 and 2 in the Monthly TAQ, and the values 00 and 01 in the Daily TAQ. In addition, I consider transactions where the sale condition is not in (O, Z, B, T, L, W, U, P).[24] Finally, I only keep transactions recorded during the trading day (i.e., from 9:30am to 4pm).

[22] As of January 2020, SPY had \$250 billion in assets under management and an average dollar volume of \$49 billion per day.

[23] See Holden, Jacobsen and Subrahmanyam (2014) for the specific dates.

[24] The sale condition excludes: opening prints; transactions reported out of sequence; bunched trades; trades executed outside of the current market hours; transactions reported to the tape at a later time; trades where the price reported is an average price; out of sequence transactions; and transactions that represent a prior reference price.

Because large marketable orders execute against multiple resting limit orders, multiple trades get printed to the tape with the same exact timestamp. I consider these multiple trades as part of one transaction, and for each timestamp, I keep the last price printed to the tape. Next, I drop observations where the tick-by-tick return exceeds 10%, which amounts to dropping 5 observations out of a total of approximately 67.4 million observations. The final sample has, on average, about 14,552 daily observations.

2.3 *Methodology*

Ultra-high frequency data tend to be contaminated by market microstructure noise, due to infrequent trading, bid-ask bounces, price discreteness, gradual response of prices to a block trade, transient liquidity issues, etc. (see, e.g., Ait-Sahalia and Yu, 2009). Therefore, at ultra-high frequency, two sources of systematic volatility risk can potentially arise: the risk embedded in the volatility of the latent fundamental return process, and the risk due to the volatility of the latent market microstructure noise process (i.e., the deviations of observed transaction prices from fundamental values). Fundamental volatility comprises random, permanent changes to the fundamentals that are revealed in the price discovery process, while transitory volatility consists of price changes that subsequently revert.[25] [26]

As said, my main focus is on the transitory volatility. To this end, I proceed to identify the volatility of the deviations between SPY's transaction prices and the latent values of the underlying portfolio of securities (and, of course, SPY shares). In what follows, I call the latent reference value of the underlying portfolio of securities (and SPY shares) the fundamental value. I formalize the assumed ultra-high frequency SPY price formation mechanism and the method for estimating SPY's transitory volatility below.

2.3.1 *Price Formation and Arbitrage at High Frequency*

Building on the intuition laid out above, I work under the assumption that the observed logarithmic SPY transaction price $\widetilde{p}_t$ (prevailing at the end of the trading day t) in the ultra-high frequency domain is the sum of a permanent fundamental component p_t, and a transitory price deviation ψ_t:

$$\widetilde{p}_t = p_t + \psi_t \qquad t = 1, 2, ..., T. \tag{1}$$

[25] In Goettler, Parlour and Rajan (2009), in equilibrium, asymmetric information creates a "volatility multiplier" because prices are too volatile relative to the fundamental asset value.

[26] As mentioned in the Introduction, theoretical models with permanent and transitory price components have been used in the market microstructure literature for some time. See, e.g., Stoll (1978), Ho and Stoll (1983), Grossman and Miller (1988), Glosten and Milgrom (1985), Kyle (1985), and Hasbrouck (1993).

The logarithmic fundamental process p_t follows the solution to the stochastic differential equation:

$$dp_t = \phi_t dt + \sigma_t dW_t. \tag{2}$$

I follow the continuous-time econometrics literature and assume that ϕ_t is a continuous predictable drift process, σ_t is a càdlàg spot volatility process bounded away from zero, that can display jumps, diurnal effects, high-persistence (possibly of the long memory type), and nonstationarities, W_t is a standard Brownian motion, and the price deviations ψ_t have zero mean and a finite fourth moment (see, e.g., Zhang, Mykland, and Ait-Sahalia, 2005; Bandi and Russell, 2008; and Barndorff-Nielsen, Hansen, Lunde and Shephard, 2008).[27] The price deviations ψ_t can be independent of the fundamental prices, but need not be, and from a market microstructure perspective, it makes sense to allow for a non-zero correlation between the two processes.[28] Based on the arguments laid out above, higher market liquidity should lead to smaller price deviations ψ_t.

Next, I divide each trading day into M (equispaced, for notational simplicity) sub-periods. The j-th intraday continuously-compounded return (or log return) between day $t-1$ and day t can be expressed as:

$$\widetilde{r}_{j,t} = \widetilde{p}_{(t-1)+j\delta} - \widetilde{p}_{(t-1)+(j-1)\delta} \qquad j = 1, 2, ..., M, \tag{3}$$

where $\delta = 1/M$ is the interval over which the intraday returns are computed. Under this notation, the fundamental price process can be expressed as:

$$p_{j,t} = p_{0,t} + \int_{(t-1)+(j-1)\delta}^{(t-1)+j\delta} \phi_s ds + \int_{(t-1)+(j-1)\delta}^{(t-1)+j\delta} \sigma_s dW_s. \tag{4}$$

Similarly to the observed price process in equation (1), the observed logarithmic return process $\widetilde{r}_{j,t}$ comprises a fundamental component, $r_{j,t}$, and a deviation component, $\nu_{j,t}$:

$$\widetilde{r}_{j,t} = r_{j,t} + \nu_{j,t}, \tag{5}$$

where

$$r_{j,t} = p_{(t-1)+j\delta} - p_{(t-1)+(j-1)\delta} \quad \text{and} \quad \nu_{j,t} = \psi_{(t-1)+j\delta} - \psi_{(t-1)+(j-1)\delta}. \tag{6}$$

The drift process in equation (4) becomes irrelevant at the ultra-high frequency, both from an economic as well as a statistical perspective (see, e.g., Ait-Sahalia, Mykland, and Zhang, 2011), so

[27] A càdlàg process is a stochastic process that is right-continuous with left limits everywhere.
[28] The derivations bellow are obtained under this less restrictive assumption.

the fundamental log return from equation (4) can be expressed as:

$$r_{j,t} = \int_{(t-1)+(j-1)\delta}^{(t-1)+j\delta} \sigma_s dW_s. \tag{7}$$

In the absence of deviations, the sum of squared returns converges in probability to the quadratic variation as $M_t \to \infty$:[29]

$$\sum_{j=1}^{M_t} \widetilde{r}_{j,t}^2 \underset{M_t \to \infty}{\xrightarrow{p}} \int_{t-1}^{t} \sigma_s^2 ds. \tag{8}$$

However, the presence of deviations leads to a substantial noise accumulation at ultra-high frequency, and the realized variation diverges as $M_t \to \infty$. This observation has led to an influential string of papers in the realized variance literature that have focused on fundamental volatility and microstructure frictions (see, e.g., Zhang, Mykland, and Ait-Sahalia, 2005; Bandi and Russell, 2006, 2008; Barndorff-Nielsen, Hansen, Lunde, and Shephard, 2008; Ait-Sahalia and Yu, 2009; Andersen, Bollerslev and Meddahi, 2011; Liu, Patton, and Sheppard 2015, among others). My approach is to focus only on the microstructure frictions and their underlying economic source.

Because uninformed agents learn from the order flow, non-negligible adjustments may occur to the transaction prices regardless of the frequency between fundamental price updates, which themselves depend on the way informed agents form expectations about future cash flows. Therefore, while the price discovery process occurs at a relatively lower frequency (because it hinges on potentially infrequent updates to the private information set), the deviations can be attributed to various frictions in the market, such as the funding constraints of financial intermediaries, and occur at a higher frequency.[30] These price deviations reflect stresses on the market-making infrastructure that cause a slow move of arbitrage capital in the high frequency domain.

The above setup implies that the magnitude of the fundamental price changes decreases with the sampling interval. It also implies that the friction returns $\nu_{j,t}$ from equation (5) do not vanish at ultra-high sampling frequencies. As a result, and following the literature, I model the deviations $\nu_{j,t}$ as having a stochastic order of magnitude $O_p(1)$. Price discreteness, bid-ask spread positioning due to dealer inventory control, and bid-ask bounces for instance, justify this assumption. Meanwhile, I assume that the fundamental return process $r_{j,t}$ has a stochastic order of magnitude $O_p(\sqrt{\delta})$, over any sub-interval of length $\delta = 1/M$. This assumption, which is standard in continuous-time asset pricing, represents slow accumulation and processing of information, leading to negligible fundamental price updates over small time intervals.[31]

[29] See, e.g, Ait-Sahalia and Yu (2009)

[30] This approach is rooted in market microstructure theory, which states that meaningful updates to fundamental prices should be less frequent than meaningful changes in transaction prices (see, e.g., O'Hara, 1995).

[31] See, e.g., Bandi and Russell (2006), and Ait-Sahalia, Mykland, and Zhang (2011).

Finally, note that the fundamental price process is a continuous stochastic semimartingale, so its increments (i.e., the fundamental log return) should be independent. Meanwhile, the empirical autocorrelogram of the high-frequency observed SPY returns supports an MA(1) structure with a negative first-order autocovariance for $\widetilde{r}_{j,t}$.[32] The departure of the observed log returns $\widetilde{r}_{j,t}$ from an i.i.d. scenario signals the presence of microstructure frictions, $\nu_{j,t}$, in the observed returns. It also supports the assumed transitory nature of the price deviations.

2.3.2 *High-Frequency Arbitrage and Market Illiquidity*

I now proceed to compute the (daily) variance of the return in equation (5):

$$Var(\widetilde{r}_{j,t}) = Var(r_{j,t}) + Var(\nu_{j,t}) \ + 2Covar(r_{j,t}, \nu_{j,t}). \tag{9}$$

Based on the above assumptions, the realized variances with the corresponding stochastic orders are:[33]

$$\sum_{j=1}^{M_t} \widetilde{r}_{j,t}^2 = \underbrace{\sum_{j=1}^{M_t} r_{j,t}^2}_{O_p(\sqrt{\delta})} + \underbrace{\sum_{j=1}^{M_t} \nu_{j,t}^2}_{O_{a.s.}(M_t)} + 2\underbrace{\sum_{j=1}^{M_t} r_{j,t}\nu_{j,t}}_{O_p(1)}. \tag{10}$$

I follow Bandi and Russell (2008) and I divide equation (11) by the daily number of observations M_t, and I take the limit as M_t approaches infinity:

$$\frac{\sum_{j=1}^{M_t} \widetilde{r}_{j,t}^2}{M_t} = \frac{\sum_{j=1}^{M_t} r_{j,t}^2}{M_t} + \frac{\sum_{j=1}^{M_t} \nu_{j,t}^2}{M_t} + 2\frac{\sum_{j=1}^{M_t} r_{j,t}\nu_{j,t}}{M_t}. \tag{11}$$

The first and third terms on the right-hand side of equation (12) will vanish based on their stochastic orders, resulting in:

$$\frac{\sum_{j=1}^{M_t} \widetilde{r}_{j,t}^2}{M_t} \underset{M_t \to \infty}{\overset{p}{\to}} \mathbf{E}(\nu_t^2) = Var(\nu_t). \tag{12}$$

It is important to note here that the estimator in equation (13) is completely different from estimators used in the literature for estimating fundamental variance, such as the 5-minute estimator, which uses the formula $V_t = \sum_{j=1}^{78} \widetilde{r}_{j,t}^2$.[34] The transitory variance estimator is computed in trade time, where trade time varies on a daily basis, while the fundamental variance is computed in clock time. There is thus no mapping between the two estimators, as M_t varies on a daily basis (which is why it has the t subscript). Therefore, the transitory variance estimator should not be perceived simply as a higher-frequency version of the fundamental variance estimator.

[32] The graph of the autocorrelogram is available upon request.

[33] The first and third terms on the right hand side of Eq. (11) are bounded in probability, while the second term is bounded almost surely. For detailed derivations, see Bandi and Russell (2008).

[34] There are 78 windows of 5-minute time length between 9:30 a.m and 4 p.m.

Finally, the result in equation (13) hinges on the fact that the fundamental returns $r_{j,t}$ are dominated by the deviation component $\nu_{j,t}$ when trades are very frequent, which is the case for the highly liquid SPY. In the limit, the deviation return variance completely swamps the variance of the fundamental return process, while the cross-term is stochastically dominated by the deviation return variance.[35] So, under realistic assumptions on the latent processes $r_{j,t}$ and $\nu_{j,t}$, $\frac{\sum_{j=1}^{M_t} \widetilde{r}_{j,t}^2}{M_t}$ consistently estimates the variance of the intraday return deviations (i.e., the transitory variance) as $M_t \to \infty$ (i.e., for a large number of intraday observations). As I employ a large number of ultra-high frequency observations per trading day (the average number of intraday returns M_t is about 14,552), I expect the consistency result in equation (13) to be fairly accurate and the corresponding estimator to be informative.

In sum, the average second moment of the observed returns sampled at the highest available frequency (i.e., in trade time) identifies the second moment of the latent intraday return deviations ν_t, which represents SPY's transitory variance. This variance is large when SPY trades away from fundamentals, which occurs when arbitrage capital is scarce. I denote by *MIL* the SPY transitory volatility.

Based on the above derivations, I propose a *daily* market illiquidity estimator (for day t), expressed in percentage points, as:

$$MIL_t = \sqrt{\frac{\sum_{j=1}^{M_t} \widetilde{r}_{j,t}^2}{M_t}}. \tag{13}$$

Because the result in equation (13) can be generalized to a monthly frequency, I also propose a *monthly* market illiquidity estimator (for month k, having T trading days), also expressed in percentage points, as:

$$MIL_k = \sqrt{\frac{\sum_{t=1}^{T} \sum_{j=1}^{M_t} \widetilde{r}_{j,t}^2}{TM_t}}. \tag{14}$$

A possible concern may arise in that the proposed illiquidity measure may be primarily driven by SPY's idiosyncratic events instead of market-wide illiquidity. To address it, I establish bellow a theoretical link between *MIL* and commonality in stock-level illiquidity, which I also empirically test in the following section.

[35] Note that this result would still hold under a jump difussion model specification for the fundamental price process.

2.3.3 *Theoretical Relation between MIL and Commonality in Stock Illiquidity*

Using the notation from equation (1), the price deviation (from the fundamental value) resulting from trading a share of stock s in the S&P500 basket at time j (on day t) can be expressed as:

$$\psi_{s,j} = \widetilde{p}_{s,j} - p_{s,j} = (1 - 2I_{sell,j})\psi^*_{s,j}, \tag{15}$$

where $\psi^*_{s,j} \geq 0$ is the cost of buying or selling, the subscript j is short for $(t-1)h + j\delta$, and I_{sell} is a sell indicator taking on the value 0 for a buy order and 1 for a sell order.[36][37] Note that the cost $\psi^*_{s,j}$ can be larger or smaller than the half bid-ask spread, because many large trades occur outside the quotes, and many small trades occur inside the quotes (see, e.g., Lee, 1993).

The price deviation resulting from trading the S&P500 portfolio at time j (which is basically the deviation of the S&P500 from fundamentals) is then a (value-weighted) average of price deviations expressed as:

$$\sum_{s=1}^{500} w_s \psi_{s,j} = (1 - 2I_{sell,j}) \sum_{s=1}^{500} w_s \psi^*_{s,j}, \tag{16}$$

where $0 < w_s < 1$ and $\sum_{s=1}^{500} w_s = 1$.

As is customary, I assume the probability that a trader is a buyer at time j is 0.5. Therefore, after taking expectations in the above expression, I obtain:

$$\mathbf{E}\left[(\sum_{s=1}^{500} w_s \psi_{s,j})\right] = \mathbf{E}\left((1 - 2I_{sell,j})\left(\sum_{s=1}^{500} w_s \psi^*_s\right)\right) = E(1 - 2I_{sell,j})E\left(\sum_{s=1}^{500} w_s \psi^*_s\right) = 0, \tag{17}$$

if the sell indicator and the individual price deviations ψ^* are independent, which is a reasonable assumption to make. Therefore, the variance of the quantity in equation (17) is:

$$Var(\sum_{s=1}^{500} w_s \psi_{s,j}) = \mathbf{E}\left[(\sum_{s=1}^{500} w_s \psi_{s,j})^2\right] = \mathbf{E}\left((1 - 2I_{sell,j})^2 \left(\sum_{s=1}^{500} w_s \psi^*_s\right)^2\right), \tag{18}$$

or,

$$Var(\sum_{s=1}^{500} w_s \psi_{s,j}) = \mathbf{E}\left[(1 - 2I_{sell,j})^2\right] \mathbf{E}\left[\left(\sum_{s=1}^{500} w_s \psi^*_s\right)^2\right], \tag{19}$$

using again the independence assumption between the sell indicator and the individual price deviations ψ^*.

[36] As is customary, I assume that buy orders occur at prices above fundamental values and sell orders occur at prices below fundamental values (see, e.g., Roll (1984)).

[37] Because this exercise focuses on the cost of trading the whole basket of S&P500 securities in exchange for the SPY, the sell indicator is not stock specific.

Because $E[(1-2I_{sell,j})]^2 = 1$ (due to the probability that a trader is a buyer at time j is 0.5), I obtain:

$$Var(\sum_{s=1}^{500} w_s \psi_{s,j}) = \mathbf{E}\left[\left(\sum_{s=1}^{500} w_s \psi_s^*\right)^2\right] = \sum_{s,u=1}^{500} w_s w_u \mathbf{E}(|\psi_s|\,|\psi_u|). \tag{20}$$

This is the variance of the portfolio price deviations (associated with buy or sell orders) from the portfolio fundamental value. This variance is large if individual stocks trade away from their fundamental value. Also, if the price deviations are cross-sectionally dependent (as is likely the case in the presence of aggregate liquidity shocks) and not identically distributed, then:

$$Var(\sum_{s=1}^{500} w_s \psi_{s,j}) = \sum_{s=1}^{500} (w_s \mathbf{E}(|\psi_s|))^2 + \sum_{s,u=1}^{500} w_s w_u \mathbf{Cov}(|\psi_s|\,,|\psi_u|). \tag{21}$$

Therefore, and as suggested by the existence of commonality in illiquidity, the pair-wise correlations ought to be taken into account when computing the variance in equation (22).[38] The simple average of value-weighted firm-specific price deviation estimates would not be an accurate estimate of the variance of the aggregate price deviations (and, therefore, the extent of market frictions) because it would not pick up the covariance terms. This is a crucial point in my quest for a market-wide illiquidity measure meant to capture commonality in stock-level illiquidity.

As argued in Section 2.1, lower aggregate liquidity may be expected to lead to larger deviations between SPY's prices and NAVs, and between the transaction prices of the underlying basket of securities and latent fundamental values. It is thus expected that SPY's price deviations (i.e., the transitory SPY price component ψ_t from equation (1)) are positively correlated to the deviations of the S&P500 Index from fundamentals. The SPY transitory price component does not need to track exactly one-for-one the quantity $\sum_{s=1}^{500} w_s \psi_{s,j}$.[39] However, as long as the two quantities are positively correlated (i.e., as long as $Var(\psi_{SPY,j}) \propto Var(\sum_{s=1}^{500} w_s \psi_{s,j})$), SPY's transitory variance does a better job in capturing the covariance terms in equation (22) and thus, in reflecting commonality in illiquidity, than the simple sum of the (squared) individual stocks price deviations (i.e., considering the first term on the right-hand side of equation (22) in isolation). Therefore, the nature of SPY and classical no-arbitrage arguments allow me to theoretically relate SPY's transitory variance to market-wide illiquidity.

Having derived the new market illiquidity proxy, I now analyze its empirical properties.

[38] For commonality in liquidity see Chordia, Roll, and Subrahmanyam (2000), Huberman and Halka (2001), Hasbrouck and Seppi (2001), Korajczyk and Sadka (2008), among others.

[39] ETFs are more liquid than individual stocks, because there is relatively little threat of adverse selection in the former group (see, e.g., Subrahmanyam, 1991).

3 Empirical Properties of the Proposed Illiquidity Measure, *MIL*

In this section I provide empirical support for the new market illiquidity measure, by showing that: *i)* it reflects illiquid times in the economy; *ii)* it is significantly correlated with existing market illiquidity proxies; *iii)* it is related to political uncertainty; *iv)* it captures commonality in stock-level illiquidity; and *v)* it provides information beyond existing illiquidity measures.

3.1 *MIL and Illiquidity Events*

Table 1 reports descriptive statistics for the daily and monthly *MIL* series, and Figure 2 displays the corresponding time series plots.[40] A visual inspection of these graphs indicates a decrease in *MIL* when decimalization got completed in the early 2001. This was expected, as the transition to the new tick size has led to an increase in liquidity (or equivalently, a decrease in illiquidity) in the market (see, e.g., Bessembinder, 2003). The plots also show a decrease in *MIL* prior to the Great Recession. More importantly, and as indicated in the bottom graph, increases in *MIL* occur during turbulent times such as: the 9/11 terrorist attack, the accounting scandals (Enron, WorldCom) and the Gulf War of 2002, the Great Recession of 2007-2009 (the bursting of the US housing bubble, accompanied by high default rates on subprime and other adjustable rate mortgages), the Flash Crash of May 2010, the U.S. debt downgrade of 2011, the emerging market crisis of 2014, the meltdown in oil prices at the beginning of 2016, the Brexit and the US-China trade war of 2017-2019.[41] Overall, these patterns support the link between *MIL* and market-wide illiquidity, with increases in *MIL* occurring during times characterized by market-wide illiquidity events.

Next step consists of comparing *MIL* to classical illiquidity proxies.

3.2 *MIL and Existing Market Illiquidity Proxies*

Alternative market illiquidity measures have, of course, been proposed. The Amihud (2002) measure aggregates stock-level "illiquidity ratios". This measure looks directly at price impacts, with the idea being that periods of illiquidity are times when small volumes are associated with large price moves. I build both the (unscaled) level in this factor, denoted by $Amih_{un}$, and the innovations in the scaled factor, denoted by $Amih$, for the period February 2001-December 2019, based on data that I download from WRDS.

Other important illiquidity proxies are the ones proposed by Hasbrouck (2009): the common factor series for effective cost, denoted by $HcTaq$ and Hz. The Hz series is a Gibbs estimate built

[40] Because the daily and monthly *MIL* measures are (the square root of) averages of second moments of high-frequency returns computed over a day, respectively a month, these statistics have similar magnitudes. And because I round up the numbers in Table 1, the daily and monthly mean and median *MIL* end up looking similar.

[41] Note that Næs, R., Skjeltorp and Ødegaard (2011) have previously linked stock market liquidity to the business cycle.

using CRSP data, while the *HcTaq* series is built based on Monthly TAQ data. I download these two effective cost series from Joel Hasbrouck's website at NYU Stern; both series end in December 2005.

Third, I employ the monthly liquidity measure proposed by Pástor and Stambaugh (2003), which is an average of stock-level liquidity. This is a price reversal measure, where less liquid stocks have larger price reversals following signed order flow, when compared to more liquid stocks. I download the level and the innovations in this factor from wrds, and I denote them by *PS* and *IPS*, respectively.

Finally, I use the Hu, Pan and Wang (2013) illiquidity measure, denoted by *HPW*, which represents an average of price deviations from asset fundamentals in the Treasury market. This measure is available on Jun Pan's website at SAIF.

Figure 3 plots the illiquidity proxies that are available over the long sample period: *MIL*, *HPW*, $Amih_{un}$, and *PS*. Most of these series display spikes during times of macro liquidity shocks, as previously identified in Figure 2, and they also experience a decrease at the beginning of the sample period.

Table 2 presents the cross-correlation matrix for these illiquidity proxies at two frequencies: daily and monthly. It is reassuring to see that *MIL* has significant (at 1% level), but not perfect correlations with existing illiquidity factors, which implies that it contains additional information compared to them. At the daily frequency, the correlation with *HPW* equals 32%, while the correlation with *HcTaq* and *Hz* equals 77% and 33%, respectively. At the monthly frequency, the correlation with *HPW* equals 44%, the correlation with $Amih_{un}$ equals 55%, while the correlation with the *HTaq* and *Hz* factors equals 88% and 47%, respectively. Note that *HPW* and $Amih_{un}$ correlate in a similar way with *HcTaq* (*Hz*), at 83% (22%) and 70% (16%), respectively. Meanwhile, *PS* has a monthly correlation ranging between -39% and -19% with the other illiquidity proxies.[42] Figure 2 of the Online Appendix displays the daily time series of the long illiquidity series, *MIL* and *HPW*.

Next step is to study the link between *MIL* and another metric for market quality, captured by political uncertainty.

3.3 *MIL and Policy Uncertainty*

Market illiquidity is a useful metric for assessing market quality. Market quality, can be affected, among other things, by political uncertainty (see, e.g., Pasquariello and Zafeiridou, 2014). Greater political uncertainty may lead to information asymmetry in the market, which could increase the adverse selection risk, as in the Grossman and Stiglitz (1980) model. While market makers may hold low inventories during times of high political uncertainty, they may still be facing the risk of

[42] Being a liquidity proxy, it was expected for *PS* to have a negative correlation with the illiquidity proxies.

information leakage. This could lead to adverse selection in the market, and to decreased liquidity provision during such times.

My hypothesis is that during times of heightened political uncertainty there is a decrease in market liquidity, or equivalently, an increase in market illiquidity. I test this hypothesis by analyzing the empirical relation between the monthly changes in *MIL* and the corresponding changes in political uncertainty, denoted by *PU*, during the period February 2001-December 2019. In doing this exercise, I also control for classical sources of risk (captured in the vector X):

$$\Delta MIL_t = \alpha + \beta \Delta PU_t + \gamma' X_t + \epsilon_t, \tag{22}$$

The proxy for *PU* is the news-based policy uncertainty index proposed by Baker, Bloom and Davis (2016).[43][44] The control variables are the Fama and French (2015) factors: *SMB*, *HML*, *RMW* and *CMA,* which are mimicking portfolios for book-to-market, equity size, operating profitability, and investment, respectively.[45] When performing this exercise, I also address the Harvey, Liu and Zhu (2016) critique by reporting both raw *p-values* and *multiplicity-adjusted p-values,* using the Benjamini and Hochberg (1995) approach, for the parameter estimates.

Table 3 reports the results. There is a significant and positive parameter estimate for PU, $\hat{\beta}$,which empirically confirms that increases (decreases) in the news based policy uncertainty are associated with increases (decreases) in market illiquidity. This relation persists when I control for the Fama and French (2015) factors. While the economic magnitude for $\hat{\beta}$ is slightly lower, its statistical significance is unaffected when including the controls in the model (adjusted *p-values* vary from 0.0002 to 0.0007).

Having connected *MIL* to macro illiquidity events, existing illiquidity factors, and policy uncertainty, next step is to empirically test its relation to commonality in stock-level illiquidity.

3.4 *MIL and Commonality in Stock Illiquidity*

I now address a possible concern that the proposed market illiquidity measure may be primarily driven by SPY's idiosyncratic events, by showing that *MIL* captures commonality in stock-level illiquidity.[46] To this end, I analyze the empirical relation between stock-level illiquidity and *MIL*. I use the daily relative quoted spread, *RSpread*, to capture stock-level illiquidity, where:

$$RSpread = (Ask - Bid)/[(Ask + Bid)/2]. \tag{23}$$

[43] The authors built the news based policy uncertainty index using a month-by-month search of 10 large U.S. newspapers for terms related to uncertainty, economy and policy. Data source: www.PolicyUncertainty.com

[44] I multiply the monthly illiquidity factor by 1,000 for the purpose of this regression.

[45] I download these factors from Ken French's website at Dartmouth.

[46] Commonality in liquidity can be caused, for instance, by the correlated trading behavior of institutional investors (see, e.g. Koch, Ruenzy, and Starks, 2016).

I build *RSpread* on a daily basis, using stock-level bid and ask data for NYSE-listed securities, which I download from the CRSP database in wrds, for the period February 2001-December 2019. I include in the sample only common stocks (share code equal to 10 or 11), that trade at least 100 shares every day, for at least 100 days, throughout the sample period. The number of firms in the sample that satisfy these requirements equals 2705.

Figure 4 displays the daily average stock-level *RSpread*. It is reassuring to see that both the daily *MIL* (from Figure 2) and average *RSpread* increase during times of financial distress. The latter result is in line with the findings in Hameed, Kang and Viswanathan (2010), who also report large increases in commonality in illiquidity during crises.

Next, I formally test whether times of market liquidity dry ups are times when (most) individual securities become less liquid. To this end, I perform an exercise similar in nature to the one in Ait-Sahalia and Yu (2009), where I run for each stock a regression of its daily changes in *RSpread* on the contemporaneous daily changes in market illiquidity, according to:

$$\Delta RSpread_{i,t} = \alpha_i + \beta_i \Delta MarketIlliq_t + \epsilon_{i,t}, \tag{24}$$

and I analyze the slope estimates. As proxies for market illiquidity, I use the two measures that are available over the period February 2001-December 2019 at a daily frequency, *MIL* and *HPW*.

Table 4 reports the results. I find that 89% of the coefficient estimates for *MIL* are positive, with 63% being positive and statistically significant. In contrast, 53% of the HPW coefficient estimates are positive, and only 11% are positive and statistically significant over the same time period. Figure 5 presents the distribution of the *T-statistics* for the slope estimates for the two regressions. The plots indicate that *MIL* has most of the mass of the distribution to the right of the 1.96 cutoff point.

These results support the hypothesis that *MIL* captures commonality in stock-level illiquidity, with times of increases in *MIL* coinciding with times of increased stock-level illiquidity across a large proportion of stocks. The second daily illiquidity measure that is available over the long time period, *HPW*, does not do a good job in capturing stock-level illiquidity. The latter result may be due to HPW being constructed in the Treasury space, which makes it more relevant for capturing bond illiquidity.[47]

The final step in this section is to prove that the proposed illiquidity measure is materially different from existing illiquidity proxies (as well as other bad times proxies).

[47] I expand on this idea in Section 5 below.

3.5 *The Novelty of MIL*

I now explore whether *MIL* is just the manifestation of other common risks. To this end, I analyze the explanatory power of existing illiquidity proxies for *MIL,* in a linear model where I regress the daily changes in *MIL* (ΔMIL) on the contemporaneous daily changes in *HPW, HZu,* and HcTaq. The daily changes in these factors are denoted by ΔHPW, ΔHZu and $\Delta HcTaq$, respectively.

Table 5 presents the results. While the coefficient estimates in all these cases are statistically significant, results show that individually, they can only explain up to 0.81% of the daily variation in ΔMIL.

Finally, Nagel (2012) shows that during times of financial market turmoil, as captured by increased values in the implied volatility index. *VIX*, market makers are reluctant to provide liquidity, and as a result, liquidity evaporates in the market. Therefore, I also explore the explanatory power of (shocks to) *VIX,* denoted by ΔVIX, for the ΔMIL factor.[48] I find that ΔVIX explains only 2.23% of the daily variation in ΔMIL. I conclude that the information contained in *MIL* is not driven by the information incorporated in existing illiquidity proxies or by the *VIX* index, which is an indication of its novelty.

Overall, the empirical evidence from this section points to the systematic nature of *MIL,* so it is natural to investigate its asset pricing ability in the next step.

4 Asset Pricing Implications for *MIL*

Most of the trading activity is handled by financial institutions, which are particularly concerned with liquidity. As a result, the literature has considered aggregate liquidity for pricing purposes for some time (see, e.g., Acharya and Pedersen, 2005; Brunnermeier and Pedersen, 2009, among others). My next step consists thus of showing that *MIL* is a novel risk factor that is not spanned by classical risk factors, including existing illiquidity proxies.

4.1 *Spanning Tests*

For this exercise, I start with building the innovations in *MIL*, based on the time series dynamics in this series. I find that an *AR(1)* model is the most parsimonious time series model that leads to no residual autocorrelation in the *MIL* series. Therefore, I build the innovations series, denoted by $IMIL_t$, as the difference between MIL_t and its time t predicted value, based on the coefficient estimates from the *AR(1)* model. Figure 6 plots the *IMIL* series.

Next, I construct a traded market illiquidity factor, by projecting *IMIL* on the space of stock returns. To this end, I download monthly returns from the CRSP database in wrds for the NYSE

[48] I download the daily values for *VIX* from the Chicago Board of Options Exchange (CBOE) for the period February 2001-December 2019.

and NYSE American common stocks (share codes 10, 11 and 12), that have a valid price at the end of the month, for the period February 2001-December 2019. I then estimate the covariance between the stock returns and *IMIL* based on Merton's (1973) intertemporal asset-pricing model (ICAPM), where *IMIL* is the state variable that captures the time variation in the investment opportunities set:

$$R^e_{i,t} = \alpha_i + \beta^m_i R^e_{m,t} + \beta^{IMIL}_i IMIL_t + \epsilon_{i,t}, \qquad i = 1, 2, ..., n. \tag{25}$$

Above, $R^e_{i,t}$ represents the excess return on stock i in period t, while $R^e_{m,t}$ is the excess return on the market portfolio in period t.

Using rolling time windows, I estimate the *IMIL* loadings on each stock i, based on the past 2 years of data (I only keep stocks that have at least 20 non-missing observations in that time window). Next, I sort stocks into ten portfolios based on their $\widehat{\beta^{IMIL}_i}$, while making sure to consider only those stocks that have valid returns over the following year.[49] For each decile portfolio, I calculate its value-weighted returns (by lagged market cap).[50] I repeat the exercise every year, and I link the portfolio returns over time.[51] Finally, I construct the traded *IMIL* factor, denoted by *Trd_IMIL*, as the difference in (value-weighted) returns between the first and the tenth decile portfolios. *Trd_IMIL* returns a significant 73 bp per month (or equivalently, around 8.76% per year) over the period 2003-2019 (*p-value* = 0.0372).

One potential explanation for the difference in returns between the first and the tenth decile is that illiquidity reflects stresses on market-making capacity, as slow moving arbitrage capital cannot be deployed during times of market stress. Assets whose returns are positively correlated with (changes in) illiquidity would provide a hedge to an investor, thereby requiring relatively lower expected returns (i.e., stocks in the tenth decile). Meanwhile, assets whose returns are negatively correlated with (changes in) illiquidity are considered relatively riskier, and require a premium to be held (i.e., stocks in the first decile). The negative relation between *IMIL* beta and the cross-section of stock returns is in line with the results in Acharya and Pedersen (2005), where the authors find that the required return of a security (while increasing in the covariance between its illiquidity and the market illiquidity) is decreasing in the covariance between the security's return and market illiquidity.

Having estimated the premium on the traded illiquidity factor, next step is to assess whether it can be explained by classical risk factors. To address it, I rely on spanning tests, as suggested by Barillas and Shanken (2017, 2018). Specifically, I estimate the abnormal returns (alphas) and

[49] The *IMIL* beta estimates are negative for the stocks in the first decile, and they are positive for the stocks in the tenth decile.

[50] I use the value-weighted approach to avoid the influence of small stocks on my results.

[51] Because I need to drop the first 2 years of data for portfolio formation, I end up with a shorter sample in this specific exercise (i.e., January 2003-December 2019).

the factor loadings for various asset pricing models in multiple regressions, where the dependent variable is *Trd_IMIL*.

I report the results in Table 6. Panel A uses the following asset pricing models: *i)* the Capital Asset Pricing Model (CAPM); *ii)* the Fama-French (1993) 3-factor model (R^e_m, *SMB* and *HML*), denoted by FF-3; *iii)* the Fama-French (2015) 5-factor model (which appends *RMW* and *CMA* to the previous model), denoted by FF-5; *iv)* the FF-5 and the Jegadeesh and Titman (1993) momentum factor, *MOM*; *v)* the FF-5 and ΔVIX. *SMB, HML, RMW* and *CMA* are mimicking portfolios for book-to-market, equity size, operating profitability, and investment, respectively. I download the returns for these portfolios and risk factors from Ken French's website at Dartmouth.

Panel B includes existing market illiquidity proxies. Specifically, it uses the following asset pricing models: *i)* the FF-5 plus the Hu, Pan and Wang (2013) factor, ΔHPW*; ii)* the FF-5 plus the Amihud residual, *Amih;* and *iii)* the FF-5 plus the traded Pastor Stambaugh factor, *PS_VWF*.[52] I account for the multiple testing problem by reporting again both raw *p-values* and *multiplicity-adjusted p-values,* using the Benjamini and Hochberg (1995) approach. The first column in each panel reports the (significant) *Trd_IMIL* premium of 73bp per month.

The first set of rows of Panel A documents the empirical failure of the CAPM in explaining the *Trd_IMIL* premium, as the model has a significant alpha estimate of 103bp per month (*adjusted p-value* = 0.0030), which is larger than the *Trd_IMIL* premium. The FF-3 and the FF-5 models from the second and third set of rows also have significant alpha estimates of 96 bp per month and 107bp per month, respectively. Adding *MOM* or ΔVIX to the FF-5 model does not help in explaining the *Trd_IMIL* premium either, as these two models also have significant alpha estimates of 104bp per month and 93bp per month, respectively. Meanwhile, Panel B shows that the FF-5 model augmented with any of the other market illiquidity proxies, ΔHPW, *Amih* or *PS_VWF,* leads to significant alpha estimates of 103bp per month, 106bp per month, and 102bp per month, respectively.

Because the alpha estimates in both panels are larger than the *Trd_IMIL* premium, these findings indicate that *Trd_IMIL* is not spanned by the classical risk factors.

4.1.1 *Robustness Checks*

To make sure that the asset pricing results reported above are not a by-product of the way I measure innovations in *MIL*, I repeat the spanning tests using an alternative approach for measuring these innovations. Specifically, I follow Hu, Pan and Wang (2013) and I use ΔMIL to capture innovations in *MIL*. Here, $\Delta = 1 - L$, where L denotes the lag operator. Next, I build an alternative traded illiquidity factor, denoted by *Trd_*Δ*MIL*, using the methodology outlined above, where I replace

[52] I download the traded Pastor Stambaugh factor from wrds.

IMIL by ΔMIL in equation (26). I find that $Trd_\Delta MIL$ carries a significant premium of 65bp per month (or equivalently, around 7.80% per year) over the period 2003-2019 (*p-value* = 0.0601).

Table 7 presents the results for the spanning tests performed using $Trd_\Delta MIL$. I find that CAPM cannot explain the premium on the traded ΔMIL factor, as it has a significant alpha estimate of 96bp per month (*adjusted p-value* = 0.0039). The FF-3 and FF5-factor models from the second and third set of rows also have significant alpha estimates of 87bp per month and 93bp per month, respectively. Adding *MOM* or ΔVIX does not help in explaining the $Trd_\Delta MIL$ premium either, as the alpha estimates in these models continue to exceed the $Trd_\Delta MIL$ premium (they are equal to 90 bp per month and 84 bp per month, respectively)

Panel B documents results obtained when augmenting the Fama-French 5-factor model with ΔHPW, *Amih* or PS_VWF. This panel shows that the resulting models yield significant alphas of 90bp per month, 93b per month, and 88bp per month, respectively. These values are again larger than the $Trd_\Delta MIL$ premium. Finally, Table 8 documents the cross-correlation matrix for the asset pricing factors.

Overall, this section documents that *MIL* is a valid risk factor. More importantly, *MIL* is not a redundant risk factor, because it is not spanned by classical factors, including existing illiquidity proxies. These findings suggest that, although related to some extent to existing illiquidity proxies, *MIL* is a novel factor that captures a different facet of market illiquidity, which I link here to the slow move of arbitrage capital in the high-frequency domain. Note that the availability of reliable intraday data limits my analyses to a relatively short sample period for the purpose of asset pricing, which in turn makes the pricing ability of *MIL* noteworthy.

5 Extending the Methodology to the Bond Market

In this section I extend the methodology used for building the stock market illiquidity measure, to the Treasury bond market. My aim here is to construct a market-wide bond illiquidity proxy using the same arguments that I presented in Section 2. To this end, I need ultra-high frequency transaction data for an instrument that tracks a Treasury index. I select the iShares Short Treasury Bond ETF, which is a liquid instrument that trades with the ticker SHV.[53] The benchmark for SHV is the ICE Short US Treasury Securities Index. SHV tracks an index composed of U.S. Treasury bonds with remaining maturities of one year or less (it has a weighted average maturity of 0.42 years). Its holdings are cash and derivatives (47.61%) and Treasuries (52.39%), which makes it a viable candidate for capturing bond market illiquidity.[54]

[53] As of April 2021, SHV has $15.92 billion of assets under management and an average dollar volume of $1.97 million per day.

[54] Detailed information on the SHV ETF can be found by visiting www.ishares.com/us/products or www.blackrock.com.

I download the ultra-high frequency SHV transaction price data from the Trade and Quote (TAQ) database in wrds for the period July 2008 - December 2019.[55] I use the same filters that I employed for the SPY series in Subsection 2.2, and I remove two outliers from the SHV price series.[56] Then, I build the transitory volatility for *SHV* using the estimator from equation (13). Because *SHV* tracks a short-maturity Treasury index, its transitory volatility is a good candidate for a market-wide funding (il)liquidity measure. I denote the transitory volatility of *SHV* by *FIL*.

Next step consists in showing that *FIL* is a viable measure of funding illiquidity, that captures commonality in bond-level illiquidity.

5.1 *FIL and Commonality in Treasury Bonds Illiquidity*

First, I assess *FIL*'s ability to capture commonality on bond-level illiquidity. I start by building the bond-level illiquidity measure, the daily relative quoted spread *RSpread,* based on equation (24) and using bond-level bid and ask data. To this end, I download data from CRSP Treasuries, for the period July 2008-December 2019. I follow Hu, Pan and Wang (2013) and drop bonds with remaining maturity of less than one month, due to possible liquidity problems, as well as bonds with maturity longer than 10 years. I also delete observations with negative yields, negative prices, or negative bid ask spreads. Finally, I keep only bonds that have at least one month of data (i.e., at least 22 observations). The final sample contains between 151 and 298 bonds per day, with an average of 251 bonds.

Next, I perform an exercise similar to the one that I did in Subsection 3.4. Specifically, I run for each bond a regression of its daily changes in *RSpread*, on the contemporaneous daily changes in a (market-wide) funding illiquidity proxy, according to:

$$\Delta RSpread_{i,t} = \alpha_i + \beta_i \Delta FundingIlliq_t + \epsilon_{i,t}, \tag{26}$$

and I analyze the slope estimates. For *FundingIlliq*, I use: *i)* the proposed bond illiquidity measure, *FIL; ii)* the *TED Spread,* which is a widely used funding (il)liquidity measure; and *iii) HPW,* which is a market-wide illiquidity measure constructed in the Treasury space. Note that Fontaine, Garcia, and Gungor (2024) have previously employed the HPW measure as a proxy for funding illiquidity. Also, the *TED Spread* represents the difference between the London Interbank Offered Rate (LIBOR) and the risk-free T-Bill rate.[57] I perform this exercise by using only days with non-missing *TED Spread* values over the period July 2008-December 2019.[58]

[55] The SHV ETF was launched on January 5, 2007. However, in order to have at least 100 daily observations my sample starts in July 2008.

[56] These observations were recorded on 12/23/2011, at approximately 15:24:56 and 15:24:57.

[57] I download the TED Spread from https://fred.stlouisfed.org.

[58] The *TED Spread* is not available for 75 days in my sample period, which represent public U.K. holidays.

Table 9 reports the results. I find that 50% of the coefficient estimates for *FIL* are positive, while the corresponding values for the *TED Spread* and *HPW* are 52% and 55%, respectively. Only a small percentage of these estimates are also significant (i.e., 7% for *FIL*, 4% for the *TED Spread,* and 8% for *HPW*), a result due to the short length of the data series. These findings indicate that *FIL* performs a similar role to the *TED Spread* and *HPW* in capturing commonality in bond-level illiquidity, which supports its role as a funding liquidity measure.

Second, I investigate the correlation between *FIL* and the other two funding illiquidity measures. When doing this exercise, I note that by construction, *MIL* is large when SPY deviates from its fundamental price, that is, when funding liquidity is low and arbitrage capital is scarce. So, *MIL* can be affected by both trading liquidity and funding liquidity. It is thus of interest to also include its correlation to the funding liquidity in this exercise.

Table 10 reports the cross-correlation matrix between the daily *FIL*, *TED Spread HPW*, and *MIL*. I find that *FIL* has significant (at 1% level) correlations of 70% and 64% with the *TED Spread* and *HPW,* respectively. Meanwhile, *HPW* has a very similar correlation with the *TED Spread,* equal to 73%. There is also a significant correlation between *FIL* and *MIL,* although of lower economic value (it only equals 36%). The *TED Spread* and *HPW* have similar correlations with *MIL,* equal to 41% and 34%, respectively. This matrix further supports the role of *FIL* as a funding illiquidity proxy. Finally, Figure 7 displays the times series of these market-wide illiquidity measures.

Having provided support for *FIL* as a market-wide funding illiquidity measure, next step is to study the cross-market dynamics of illiquidity. When performing this exercise, I also analyze the relation between illiquidity and market volatility.

5.2 *The Relation between Market Illiquidity, Funding Illiquidity, and Market Volatility*

Theoretical asset pricing models, such as the one in Brunnermeier and Pedersen (2009), posit that during times of market stress, decreases in market liquidity and funding liquidity reinforce each other, leading to "liquidity spirals". The Brunnermeier and Pedersen model also predicts that market liquidity declines as fundamental volatility increases.[59] Furthermore, the theoretical model in Gromb and Vayanos (2002) predicts that higher volatility tightens funding constraints of market makers, and thereby reduces their liquidity-provision capacity. It is thus important to examine the empirical relation between market (il)liquidity, funding (il)liquidity, and market volatility.

I capture the relationship between market illiquidity, funding illiquidity, and market volatility

[59] The link between volatility and liquidity can also be found in the models of Grossman and Miller (1988), Vayanos (2004), among others. Also, Chordia, Sarkar, and Subrahmanyam (2005) document cross-markets dynamics between volatility and liquidity.

using a vector autoregression (VAR) model, where I look separately at three scenarios: *i)* market illiquidity and funding illiquidity; *ii)* funding illiquidity and market volatility; and *iii)* market illiquidity and market volatility. For each scenario, I model the relationship between the two series of interest using a VAR model that captures their dynamic relation over time. I use *MIL* to capture market illiquidity, *FIL* to capture funding illiquidity, and *VIX* to proxy for market volatility in the main exercise. The VAR model is thus fitted for three pairs of factors: (*MIL*, *FIL*), (*FIL*, *VIX*), and (*MIL*, *VIX*), as follows.

Let $F_t = (F_{1,t}, F_{2,t})'$ denote a 2-dimensional time series vector of daily factors, where the factors F_i belong to the set {*MIL, FIL, VIX*}, for i = 1, 2. The VAR(p) process can be written as:

$$F_t = \delta + \Phi_1 F_{t-1} + ... + \Phi_p F_{t-p} + \varepsilon_t, \tag{27}$$

where $\epsilon_t = (\epsilon_1, \epsilon_2)_t'$ is a white noise process with $E(\epsilon_t) = 0$, $E(\epsilon_t \epsilon_{t-p}^{'}) = 0$ (there is no serial correlation in the individual error terms), and $E(\epsilon_t \epsilon_t^{'}) = \Sigma = \begin{pmatrix} \sigma_{11}^1 & \sigma_{12}^1 \\ \sigma_{21}^1 & \sigma_{22}^1 \end{pmatrix}$ represents the positive-semidefinite contemporaneous covariance matrix of the error terms. $\Phi_i = \begin{pmatrix} \phi_{11}^i & \phi_{12}^i \\ \phi_{21}^i & \phi_{22}^i \end{pmatrix}$ is a *2x2* matrix of parameters to be estimated for every $i = 1, ..., p$. I use the Toda and Yamamoto (1995) procedure, which requires the estimation of an augmented VAR that guarantees the asymptotic distribution of the Wald statistic (an asymptotic χ^2 distribution), as the testing procedure is robust to the integration and cointegration properties of the process. I end up selecting a VAR(3) model for all three scenarios.

Table 11 reports the results for the χ^2 test for establishing Granger causality (i.e., in the Panel with the label *"Funding Illiquidity$\nRightarrow$Market Illiquidity"* I test the null hypothesis that funding illiquidity does not Granger cause market illiquidity), and the associated *p-value*. The first set of rows of Panel A show that I can reject at the 1% level the hypotheses that funding illiquidity and market illiquidity do not Granger cause each other. These results support the theoretical model in Brunnermeier and Pedersen (2009). They indicate that, when funding liquidity is tight, traders become reluctant to take on positions, which lowers market liquidity. This in turn leads to higher margins and funding constraints (via increases in fundamental volatility).

The second set of rows show that I can reject at the 1% level the hypotheses that funding illiquidity and market volatility do not Granger cause each other. The economic explanation here is that a tightening in funding liquidity restricts market makers' trading activity, which slows down price discovery and increases the uncertainty in asset valuation. Conversely, during turbulent times, there is higher uncertainty about asset valuation in the market, which increases adverse selection and leads to decreased liquidity provision. The latter causality result supports the theoretical model in Gromb and Vayanos (2002).

The third set of rows in Panel A indicate that I cannot reject at the 1% level the hypothesis that market illiquidity does not Granger cause market volatility. However, I can reject the hypothesis that market volatility does not Granger cause market illiquidity. The latter result provides empirical support to the Brunnermeier and Pedersen (2009) model, where market liquidity declines as fundamental volatility increases. My finding is also in line with the empirical results in Chordia, Sarkar, and Subrahmanyam (2005), who show that positive volatility innovations in stock (and bond) markets predict an increase in quoted spreads and a reduction of depth in those markets. Finally, my result is in line with the findings in Nagel (2012), who shows that during times of financial market turmoil, as captured by increased values in the implied volatility index *VIX*, market makers are reluctant to provide liquidity, and as a result, liquidity evaporates in the market.

5.2.1 *Robustness Checks*

Next step consists of verifying the robustness of these findings by using the *TED Spread* to capture funding illiquidity. Because the *TED Spread* has missing data during U.K. public holidays, the sample used for this specific exercise has a smaller number of observations (the *TED Spread* has 75 missing observations over my sample period).

Results reported in Panel B of Table 11 show that my findings are robust to the choice of funding illiquidity proxy. Market illiquidity and funding illiquidity continue to reinforce each other, as do funding illiquidity and market volatility. Also as above, market volatility Granger causes market illiquidity.

In sum, this section demonstrates that a realistic market-wide funding illiquidity measure can be build at the aggregate level based only on U.S. data. Compared to the *TED Spread, FIL* provides the advantage of being traded in the U.S. markets, and thus, of being a good gauge of funding illiquidity during times when the *TED Spread* is not available, which occurs 75 times in my sample period. Compared to the *HPW* measure, *FIL* is extracted at the aggregate level, so it is not dependent on bond-level transaction data. More importantly, intraday measures of funding illiquidity can be easily computed as the *SHV* ETF is a highly traded security. The intra-daily availability of *FIL* also points to its advantage versus the Secured Overnight Financing Rate (SOFR) which has been recently proposed (after the sample period used here) as the alternative to LIBOR for the new USD derivatives and other financial contracts.[60]

[60] The New York Fed is publishing daily values for the SOFR index, as a well as a "30-day Average SOFR," a "90-day Average SOFR," and an "180-day Average SOFR" . See the New York Fed communication on the transition from LIBOR to SOFR at https://www.newyorkfed.org/arrc/sofr-transition

6 Conclusions

Transitory volatility captures asset price distortions (deviations from fundamental values) caused by a deterioration in high-frequency arbitrage capital. More critically, it signals pressures within the market-making infrastructure, which can destabilize the securities markets. As such, transitory volatility is of first-order importance to market participants, and I show that it serves as an effective measure of illiquidity.

Specifically, I derive a market-wide illiquidity measure based on SPY's transitory volatility, combining continuous-time econometrics, no-arbitrage arguments, and market microstructure theory. Using high-frequency SPY transaction data, I empirically construct this measure in trade time and demonstrate that it captures commonality in stock-level illiquidity. Additional empirical evidence supports its relevance, showing strong connections with market-wide illiquidity events, traditional illiquidity factors, and political uncertainty. Despite these correlations, the proposed measure is notably distinct from conventional illiquidity proxies, as it does not rely on stock-level trading volume, nor does it aggregate firm-level data. Moreover, it provides real-time information on market illiquidity.

Interestingly, this illiquidity measure functions as a priced risk factor. Sorting stocks by their exposure to this factor generates a significant annual return spread of approximately 8.76%, which cannot be explained by traditional risk factors, including existing illiquidity measures. Therefore, if investors are concerned with market frictions due to the slow movement of arbitrage capital, alongside changes in equilibrium asset values and other factors, my findings suggest that incorporating this illiquidity measure into asset pricing models may be valuable.

Furthermore, I demonstrate the portability of the methodology used in this paper to a different asset class. Specifically, I extend the transitory volatility estimator to the Treasury market by creating a funding illiquidity measure based on a bond ETF, and I document cross-markets liquidity dynamics.

Finally, using high-frequency ETF transaction prices and the methodology outlined here for illiquidity estimation proves to be computationally and economically efficient. It is essential for financial risk managers to anticipate and manage liquidity risk, and those already calculating the risk-neutral density of returns implied by option prices may find the proposed illiquidity measure helpful for assessing changes in market-wide liquidity. In today's uncertainty-ridden markets, investors are increasingly focused on hedging against liquidity shocks, and a real-time illiquidity measure can be crucial. Moreover, the proposed illiquidity factor may aid in predicting "flash crash"-like events. While I leave these applications for future research, I hope my findings will encourage further research using the proposed illiquidity measure.

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Table 1: Descriptive Statistics for the Market Illiquidity Proxies

This table reports descriptive statistics for daily and monthly illiquidity proxies: the proposed market illiquidity measure (*MIL),* expressed in %, the Hu, Pan and Wang (2013) illiquidity measure (*HPW)*, the Amihud illiquidity factor (*Amih*), the two Hasbrouck illiquidity factors (*HcTaq* and *Hz)*, and the Pastor-Stambaugh liquidity measure (*PS)*. Data cover the period February 2001-December 2019, except for the *HPW* series (ending in September 2019) and the *HcTaq* and *Hz* series (ending in December 2005).

Panel A: Descriptive Statistics for the Daily Factors					
	Mean	Median	Std Dev	Skewness	Kurtosis
MIL	0.02	0.01	0.02	3.62	22.21
HPW	0.03	0.02	0.02	4.06	19.80
HcTaq	0.01	0.01	0.00	0.75	-0.37
Hz	0.30	0.15	0.35	2.72	9.57

Panel B: Descriptive Statistics for the Monthly Factors					
	Mean	Median	Std Dev	Skewness	Kurtosis
MIL	0.02	0.01	0.01	2.32	7.30
HPW	0.03	0.02	0.02	4.06	19.71
Amih	0.06	0.06	0.02	1.60	4.22
HcTaq	0.01	0.01	0.00	0.66	-0.75
Hz	0.30	0.19	0.25	2.04	4.25
PS	-0.02	-0.01	0.06	-1.30	3.86

Table 2: Cross-Correlations between Market Illiquidity Proxies

This table reports the daily and monthly cross-correlations for the following (il)liquidity proxies: the new market illiquidity measure (*MIL)*, the Hu, Pan and Wang (2013) illiquidity measure (*HPW)*, the Amihud illiquidity factor (*Amih*), the two Hasbrouck illiquidity factors *(HcTaq* and *Hz)*, and the Pastor-Stambaugh liquidity factor (*PS)*. I also include the correlations of the (il)liquidity proxies with the implied volatility index (*VIX)*. Data cover the period February 2001-December 2019, except for the *HPW* series (ending in September 2019) and the *HcTaq* and *Hz* series (ending in December 2005). I use ***, ** and * to indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Cross-Correlations of Daily Factors

	MIL	*HPW*	*HcTaq*	*Hz*	*VIX*
MIL	1				
HPW	0.32***	1			
HcTaq	0.77***	0.74***	1		
Hz	0.33***	0.14***	0.34***	1	
VIX	0.50***	0.76***	0.81***	0.32***	1

Panel B: Cross-Correlations of Monthly Factors

	MIL	*HPW*	*Amih*	*HcTaq*	*Hz*	*PS*	*VIX*
MIL	1						
HPW	0.44***	1					
Amih	0.55***	0.52***	1				
HcTaq	0.88***	0.83***	0.70***	1			
Hz	0.47***	0.22***	0.16	0.42***	1		
PS	-0.33***	-0.33***	-0.39***	-0.19	-0.42***	1	
VIX	0.62***	0.75***	0.59***	0.82***	0.41***	-0.37***	1

Table 3: *MIL* and Policy Uncertainty

This table reports the parameter estimates from linear regressions of monthly changes in the new market illiquidity factor *MIL,* on the monthly changes in the news-based policy uncertainty index from Baker, Bloom and Davis (2016) (denoted by *PU* and downloaded from www.PolicyUncertainty.com). The regressions also control for the excess market return and the Fama-French (2015) factors *SMB*, *HML*, *RMW* and *CMA* factors, which represent mimicking portfolios for equity size, book-to-market, operating profitability, and investment, respectively. I multiply the monthly market illiquidity measure by a factor of 1,000 for the purpose of this exercise. Data cover the period March 2001-December 2019. I report the raw *p-values* in parentheses, and the *multiplicity-adjusted p-values,* using the Benjamini and Hochberg (1995) approach, in brackets. I report the R^2_{adj} in percentages. I use ***, ** and * to indicate statistical significance at the 1%, 5% and 10% levels, respectively, based on the *multiplicity-adjusted p-values*.

Intercept	$\widehat{\beta}_{\Delta PU}$	$\widehat{\beta}_{m}$	$\widehat{\beta}_{SMB}$	$\widehat{\beta}_{HML}$	$\widehat{\beta}_{RMW}$	$\widehat{\beta}_{CMA}$	$R^2_{adj}(\%)$
-0.30	0.07***						11.66
(0.5843)	*(0.0001)*						
[0.5843]	*[0.0002]*						
0.14	0.06***	-0.53***	-0.40*	0.59***			20.81
(0.7933)	*(0.0001)*	*(0.0001)*	*(0.0677)*	*(0.0053)*			
[0.7933]	*[0.0003]*	*[0.0003]*	*[0.0846]*	*[0.0088]*			
0.22	0.05***	-0.57***	-0.47*	0.46	-0.34	0.50	21.36
(0.6791)	*(0.0001)*	*(0.0002)*	*(0.0339)*	*(0.0583)*	*(0.2435)*	*(0.1631)*	
[0.6791]	*[0.0007]*	*[0.0007]*	*[0.0791]*	*[0.1020]*	*[0.2841]*	*[0.2283]*	

Table 4: Market Illiquidity Proxies and Commonality in Stock Illiquidity

This table reports statistics for the slope estimates in linear regressions, where daily changes in stock-level relative quoted spread are regressed on the contemporaneous daily changes in market illiquidity. The relative quoted spread is defined as *RSpread = (Ask-Bid)/[(Ask+Bid)/2].* As proxies for the market illiquidity, I use the new factor, *MIL*, and the Hu, Pan and Wang (2013) factor, *HPW*. I include in the sample only NYSE-listed common stocks (i.e., share code equal to 10 or 11), that trade at least 100 shares per day, every day, for at least 100 days, during the period of interest. The number of firms equals 2705. Data cover the period February 2001 - December 2019.

	MIL	*HPW*
% positive $\widehat{\beta}_i$	89%	53%
% positive and significant (at the 5% level) $\widehat{\beta}_i$	63%	11%
Mean |T-stat| for $\widehat{\beta}_i$	3.95	1.16

Table 5: *MIL* Novelty

This table reports the estimates from a time series regression of daily changes in the new market illiquidity proxy (ΔMIL) on the contemporaneous daily changes in: the Hu, Pan and Wang (2013) illiquidity measure (ΔHPW), the Hasbrouck measures (ΔHz and $\Delta HcTaq$), and the implied volatility index (ΔVIX). In this exercise, I multiply ΔMIL by 100. I report the R^2_{adj} in percentages. Data start in February 2001, and they end in December 2019 for the *VIX* and *HPW* measures, and on December 2005 for the *HcTaq* and *Hz* measures. I report the *p-values* in parentheses. I use ***, ** and * to indicate statistical significance at the 1%, 5% and 10% levels, respectively.

ΔHPW	ΔHz	$\Delta HcTaq$	ΔVIX	$R^2_{adj}(\%)$
35.83***				0.52
(0.0001)				
	0.58***			0.81
	(0.0009)			
		188.50***		0.66
		(0.0025)		
			0.12***	2.23
			(0.0001)	

Table 6: Spanning Tests for the Traded Factor

This table reports the average return for the traded illiquidity factor, denoted by *Trd_IMIL*, in the first column, and the results from spanning regressions in the other columns. *IMIL* is the monthly innovation in MIL (i.e., the residual from an $AR(1)$ model applied to the *MIL* series). The traded illiquidity factor, *Trd_IMIL,* is the difference between the lowest *IMIL*-sensitivity portfolio and the highest *IMIL*-sensitivity one (in a 2-factor model that also control for market risk). The table reports the intercept and factor loadings from spanning regressions, where *Trd_IMIL* is regressed on the excess market return, the *SMB, HML, RMW* and *CMA* factors of Fama-French (2015) (i.e., the mimicking portfolios for equity size, book-to-market, operating profitability, and investment, respectively), the momentum factor of Jegadeesh and Titman (1993), *MOM*, the changes in the implied volatility index, ΔVIX, the changes in the Hu, Pan and Wang (2013) illiquidity measure, ΔHPW, the Amihud residual, *Amih*, and the traded Pastor-Stambaugh (2003) factor, *PS_VWF*. I report results in percentages, on a monthly basis. Data cover the period January 2003-December 2019. I report the raw *p-values* in parentheses, and the *multiplicity-adjusted p-values,* using the Benjamini and Hochberg (1995) approach, in brackets. I report the R^2_{adj} in percentages. I use ***, ** and * to indicate statistical significance at the 1%, 5% and 10% levels, respectively, based on the *multiplicity-adjusted p-values*.

Panel A: Explaining the Traded *IMIL* Factor using the Fama-French 5 Factors, Momentum, and *VIX*									
$\overline{R}$	$\widehat{\alpha}$	$\widehat{\beta}_m$	$\widehat{\beta}_{SMB}$	$\widehat{\beta}_{HML}$	$\widehat{\beta}_{RMW}$	$\widehat{\beta}_{CMA}$	$\widehat{\beta}_{MOM}$	$\widehat{\beta}_{\Delta VIX}$	$R^2_{adj}(\%)$
0.73**	1.03***	-0.36***							7.93
(0.0372)	*(0.0030)*	*(0.0001)*							
	[0.0030]	*[0.0002]*							
	0.96***	-0.35***	0.25	-0.45***					12.05
	(0.0047)	*(0.0001)*	*(0.1059)*	*(0.0015)*					
	[0.0063]	*[0.0004]*	*[0.1059]*	*[0.0030]*					
	1.07***	-0.40***	0.18	-0.46***	-0.34	0.04			12.26
	(0.0023)	*(0.0001)*	*(0.2655)*	*(0.0050)*	*(0.1267)*	*(0.8873)*			
	[0.0069]	*[0.0006]*	*[0.3186]*	*[0.0100]*	*[0.1901]*	*[0.8873]*			
	1.04***	-0.35***	0.17	-0.34*	-0.36	0.02	0.18*		13.85
	(0.0028)	*(0.0007)*	*(0.3000)*	*(0.0468)*	*(0.1055)*	*(0.9504)*	*(0.0324)*		
	[0.0098]	*[0.0049]*	*[0.3500]*	*[0.0819]*	*[0.1477]*	*[0.9504]*	*[0.0756]*		
	0.93**	-0.24	0.19	-0.52**	-0.31	0.07		0.19	13.18
	(0.0085)	*(0.0821)*	*(0.2477)*	*(0.0019)*	*(0.1707)*	*(0.8078)*		*(0.0800)*	
	[0.0298]	*[0.1437]*	*[0.2890]*	*[0.0133]*	*[0.2390]*	*[0.8078]*		*[0.1437]*	

Panel B: Explaining the Traded *IMIL* Factor using the Fama-French 5 Factors and Existing Illiquidity Proxies										
$\overline{R}$	$\widehat{\alpha}$	$\widehat{\beta}_m$	$\widehat{\beta}_{SMB}$	$\widehat{\beta}_{HML}$	$\widehat{\beta}_{RMW}$	$\widehat{\beta}_{CMA}$	$\widehat{\beta}_{\Delta HPW}$	$\widehat{\beta}_{Amih}$	$\widehat{\beta}_{PS_VWF}$	$R^2_{adj}(\%)$
0.73**	1.03**	-0.39***	0.18	-0.45**	-0.35	0.03	15.40			11.86
(0.0372)	*(0.0034)*	*(0.0002)*	*(0.2708)*	*(0.0068)*	*(0.1226)*	*(0.9200)*	*(0.7513)*			
	[0.0119]	*[0.0014]*	*[0.3791]*	*[0.0159]*	*[0.2146]*	*[0.9200]*	*[0.8765]*			
	1.06***	-0.37***	0.18	-0.47**	-0.34	0.05		17.32		12.09
	(0.0025)	*(0.0004)*	*(0.2778)*	*(0.0044)*	*(0.1316)*	*(0.8670)*		*(0.4355)*		
	[0.0088]	*[0.0028]*	*[0.3889]*	*[0.0103]*	*[0.2303]*	*[0.8670]*		*[0.5081]*		
	1.02**	-0.42***	0.09	-0.38**	-0.33	0.13			28.94**	15.25
	(0.0029)	*(0.0001)*	*(0.5650)*	*(0.0219)*	*(0.1324)*	*(0.6286)*			*(0.0052)*	
	[0.0102]	*[0.0007]*	*[0.6286]*	*[0.0383]*	*[0.1854]*	*[0.6286]*			*[0.0121]*	

Table 7: Robustness Checks for Spanning Tests using the Second Market Illiquidity Shock

This table reports the average return for the alternative traded illiquidity factor, denoted by *Trd_ ΔMIL*, in the first column, and the results from spanning regressions in the other columns. *ΔMIL* represents the monthly shocks to the illiquidity series *MIL*, where $\Delta = 1 - L$, and L denotes the lag operator. This alternative traded illiquidity factor, *Trd_ ΔMIL,* is the difference between the lowest ΔMIL-sensitivity portfolio and the highest ΔMIL-sensitivity one (in a 2-factor model that also control for market risk). The table reports the intercept and factor loadings from spanning regressions, where *Trd_ ΔMIL* is regressed on the excess market return, the *SMB, HML, RMW* and *CMA* factors of Fama-French (2015) (i.e., the mimicking portfolios for equity size, book-to-market, operating profitability, and investment, respectively), the momentum factor of Jegadeesh and Titman (1993), *MOM*, the changes in the implied volatility index, ΔVIX, the changes in the Hu, Pan and Wang (2013) illiquidity measure, ΔHPW, the Amihud residual, *Amih*, and the traded the Pastor-Stambaugh (2003) factor, *PS_ VWF*. I report results in percentages, on a monthly basis. Data cover the period February 2001-December 2019. I report the raw *p-values* in parentheses, and the *multiplicity-adjusted p-values,* using the Benjamini and Hochberg (1995) approach, in brackets. I report the R^2_{adj} in percentages. I use ***, ** and * to indicate statistical significance at the 1%, 5% and 10% levels, respectively, based on the *multiplicity-adjusted p-values*.

Panel A: Explaining the Traded ΔMIL Factor using the Fama-French 5 Factors, Momentum, and *VIX*									
$\overline{R}$	$\widehat{\alpha}$	$\widehat{\beta}_m$	$\widehat{\beta}_{SMB}$	$\widehat{\beta}_{HML}$	$\widehat{\beta}_{RMW}$	$\widehat{\beta}_{CMA}$	$\widehat{\beta}_{MOM}$	$\widehat{\beta}_{\Delta VIX}$	$R^2_{adj}(\%)$
0.65**	0.96***	-0.38***							9.33
(0.0601)	*(0.0043)*	*(0.0001)*							
	[0.0039]	*[0.0002]*							
	0.87***	-0.35***	0.22	-0.55***					15.84
	(0.0074)	*(0.0001)*	*(0.1412)*	*(0.0001)*					
	[0.0099]	*[0.0002]*	*[0.1412]*	*[0.0002]*					
	0.93**	-0.37***	0.15	-0.62***	-0.28	0.24			16.22
	(0.0051)	*(0.0001)*	*(0.3276)*	*(0.0001)*	*(0.1953)*	*(0.3594)*			
	[0.0102]	*[0.0003]*	*[0.3594]*	*[0.0003]*	*[0.2930]*	*[0.3594]*			
	0.90**	-0.31***	0.14	-0.48**	-0.30	0.21	0.21**		18.65
	(0.0062)	*(0.0013)*	*(0.3749)*	*(0.0030)*	*(0.1588)*	*(0.4059)*	*(0.0092)*		
	[0.0145]	*[0.0091]*	*[0.4059]*	*[0.0105]*	*[0.2223]*	*[0.4059]*	*[0.0161]*		
	0.84**	-0.26	0.16	-0.66***	-0.25	0.26		0.13	16.47
	(0.0132)	*(0.0451)*	*(0.3141)*	*(0.0001)*	*(0.2391)*	*(0.3228)*		*(0.2080)*	
	[0.0462]	*[0.1052]*	*[0.3228]*	*[0.0007]*	*[0.3228]*	*[0.3228]*		*[0.3228]*	

Panel B: Explaining the Traded ΔMIL Factor using the Fama-French 5 Factors and Existing Illiquidity Proxies

$\overline{R}$	$\widehat{\alpha}$	$\widehat{\beta}_m$	$\widehat{\beta}_{SMB}$	$\widehat{\beta}_{HML}$	$\widehat{\beta}_{RMW}$	$\widehat{\beta}_{CMA}$	$\widehat{\beta}_{\Delta HPW}$	$\widehat{\beta}_{Amih}$	$\widehat{\beta}_{PS_VWF}$	$R^2_{adj}(\%)$
0.65**	0.90***	-0.36***	0.15	-0.61***	-0.29	0.21	33.65			16.05
(0.0601)	*(0.0075)*	*(0.0003)*	*(0.3325)*	*(0.0001)*	*(0.1752)*	*(0.4353)*	*(0.4670)*			
	[0.0175]	*[0.0011]*	*[0.4655]*	*[0.0007]*	*[0.3066]*	*[0.4670]*	*[0.4670]*			
	0.93**	-0.36***	0.15	-0.63***	-0.27	0.24		10.23		15.89
	(0.0054)	*(0.0004)*	*(0.3370)*	*(0.0001)*	*(0.2001)*	*(0.3523)*		*(0.6296)*		
	[0.0126]	*[0.0014]*	*[0.4110]*	*[0.0007]*	*[0.3502]*	*[0.4110]*		*[0.6296]*		
	0.88***	-0.39***	0.05	-0.53***	-0.26	0.34**			32.60***	25.85
	(0.0065)	*(0.0001)*	*(0.7291)*	*(0.0007)*	*(0.2043)*	*(0.1814)*			*(0.0009)*	
	[0.0114]	*[0.0007]*	*[0.7291]*	*[0.0021]*	*[0.2384]*	*[0.2384]*			*[0.0021]*	

Table 8: Cross-Correlations Between Asset Pricing Factors

This table reports the correlations between the monthly traded risk factors. R_m^e is the excess market return, while *Trd_IMIL and Trd_*Δ*MIL* are the traded illiquidity factors. *SMB, HML, RMW*, and *CMA* are the Fama and French (2015) mimicking portfolios for equity size, book-to-market, operating profitability, and investment, respectively. *MOM* is the momentum factor of Jegadeesh and Titman (1993), *PS_VWF* is the traded Pastor-Stambaugh liquidity factor, *Amih* is the Amihud residual. ΔHPW and ΔVIX represent the monthly innovations in the Hu, Pan and Wang (2013) factor and the implied volatility index, respectively. Data cover the period January 2003-December 2019 (*Trd_IMIL* starts in January 2003). I use ***, ** and * to denote significance at the 1%, 5% and 10% levels, respectively.

	R_m^e	Trd_IMIL	$Trd_\Delta MIL$	SMB	HML	RMW	CMA	MOM	ΔHPW	$Amih$	PS_VWF	ΔVIX
R_m^e	1											
Trd_IMIL	-0.29***	1										
$Trd_\Delta MIL$	-0.31***	0.95***	1									
SMB	0.42***	-0.06	-0.09	1								
HML	0.25***	-0.26***	-0.32***	0.26***	1							
RMW	-0.42***	0.01	0.04	-0.41***	-0.14**	1						
CMA	-0.03	-0.06	-0.05	0.13*	0.49***	-0.12*	1					
MOM	-0.35***	0.29***	0.34***	-0.17**	-0.41**	0.18**	-0.13*	1				
ΔHPW	-0.39***	0.12*	0.16**	-0.13*	-0.06	0.18***	0.17**	0.29***	1			
$Amih$	-0.31***	0.13*	0.11	-0.09	-0.02	0.10	0.02	0.10	0.28***	1		
PS_VWF	0.12*	0.20***	0.23***	0.18**	-0.21***	-0.09	-0.21***	0.15**	-0.19***	-0.20***	1	
ΔVIX	-0.74***	0.26***	0.25***	-0.26***	-0.09	0.27***	0.10	0.16**	0.21***	0.28***	-0.11	1

Table 9: Funding Illiquidity Proxies and Commonality in Bond Illiquidity

This table reports statistics for the slope estimates in linear regressions, where daily changes in bond-level relative quoted spread are regressed on the contemporaneous daily changes in funding illiquidity proxies. The relative quoted spread is defined as *RSpread = (Ask-Bid)/[(Ask+Bid)/2]*. As proxies for funding illiquidity, I use the new factor, *FIL* (i.e., the measure built based on the transitory volatility of the *SHV* Treasury bond ETF), the *TED Spread* (i.e., the difference between the London Interbank Offered Rate, LIBOR, and the risk-free T-Bill rate), and the Hu, Pan and Wang (2013) factor, *HPW*. I include in the sample only Treasury bonds that have a remaining maturity of at least one month and at most 10 years. Data cover the period July 2008 - December 2019.

	FIL	*TED Spread*	*HPW*
% positive $\widehat{\beta}_i$	50%	52%	55%
% positive and significant (at the 5% level) $\widehat{\beta}_i$	7%	4%	8%
Mean |T-stat| for $\widehat{\beta}_i$	0.94	0.94	1.07

Table 10: Cross-Correlations Between Illiquidity Proxies

This table reports the cross-correlations between the daily values of *FIL* (i.e., the funding illiquidity proxy built based on the transitory volatility of the *SHV* Treasury bond ETF), *TED Spread* (i.e., the difference between the London Interbank Offered Rate, LIBOR, and the risk-free T-Bill rate), Hu, Pan and Wang (2013) factor, *HPW,* and *MIL* (i.e., the market illiquidity proxy built based on the transitory volatility of the SPY ETF). Data cover the period July 2008 - December 2019. I use ***, ** and * to indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	FIL	*TED Spread*	*HPW*	*MIL*
FIL	1			
TED Spread	0.70***	1		
HPW	0.64***	0.73***	1	
MIL	0.36***	0.41***	0.34***	1

Table 11: Market Illiquidity, Funding Illiquidity, and Market Volatility

This table reports results for Granger causality tests between daily market illiquidity, funding illiquidity and market volatility. The null hypothesis below, H_0*:* $X \nRightarrow Y$, is that X does not Granger cause Y. I use *MIL* (i.e., the market illiquidity proxy built based on the transitory volatility of the SPY ETF) to capture market illiquidity, and *VIX* to proxy for market volatility. I use *FIL* (i.e., the measure built based on the transitory volatility of the Treasury bond ETF, SHV) to measure funding illiquidity in Panel A, and the *TED Spread* (i.e., the difference between the London Interbank Offered Rate, LIBOR, and the risk-free T-Bill rate) to proxy for funding illiquidity in Panel B. I report the *chi-square* and *p-value* for each test. Results are obtained using a VAR(3) specification based on the Toda and Yamamoto (1995) method. Data cover the period July 2008 - December 31, 2019. Panel B has a smaller number of observations, because the *TED Spread* has 75 missing values, corresponding to U.K. public holidays.

Panel A: Using *SHV*'s Transitory Volatility to Proxy for Funding Illiquidity (No of obs=2896)			
H_0*: Funding Illiquidity* $\nRightarrow$ *Market Illiquidity*		H_0*: Market Illiquidity* $\nRightarrow$ *Funding Illiquidity*	
χ^2	432.35	χ^2	14.17
p-value	<0.0001	*p-value*	0.0027
H_0*: Funding Illiquidity* $\nRightarrow$ *Market Volatility*		H_0*: Market Volatility* $\nRightarrow$ *Funding Illiquidity*	
χ^2	78.11	χ^2	107.10
p-value	<0.0001	*p-value*	<0.0001
H_0*: Market Illiquidity* $\nRightarrow$ *Market Volatility*		H_0*: Market Volatility* $\nRightarrow$ *Market Illiquidity*	
χ^2	3.66	χ^2	515.84
p-value	0.3008	*p-value*	<0.0001

Panel B: Using the *TED Spread* to Proxy for Funding Illiquidity (No of obs=2821)			
H_0: *Funding Illiquidity* $\nRightarrow$ *Market Illiquidity*		H_0: *Market Illiquidity* $\nRightarrow$ *Funding Illiquidity*	
χ^2	237.40	χ^2	21.11
p-value	<0.0001	*p-value*	<0.0001
H_0: *Funding Illiquidity* $\nRightarrow$ *Market Volatility*		H_0: *Market Volatility* $\nRightarrow$ *Funding Illiquidity*	
χ^2	24.79	χ^2	15.76
p-value	<0.0001	*p-value*	0.0013
H_0: *Market Illiquidity* $\nRightarrow$ *Market Volatility*		H_0: *Market Volatility* $\nRightarrow$ *Market Illiquidity*	
χ^2	3.18	χ^2	497.98
p-value	0.3640	*p-value*	<0.0001

Figure 1: Price Behavior of an ETP During the Mini Flash Crash of August 24, 2015
This figure plots the prices for an exchange traded product (ETP) and the Index that it tracks, around the Mini Flash Crash event of August 24, 2005. Note that the primary and secondary axes use different scales. The purple line (i.e., the line below) represents the ETP price, and the orange line (the line above) is the Index price. Source: The BlackRock Report on the August 24 Flash Crash available at https://www.sec.gov/comments/265-29/26529-52.pdf

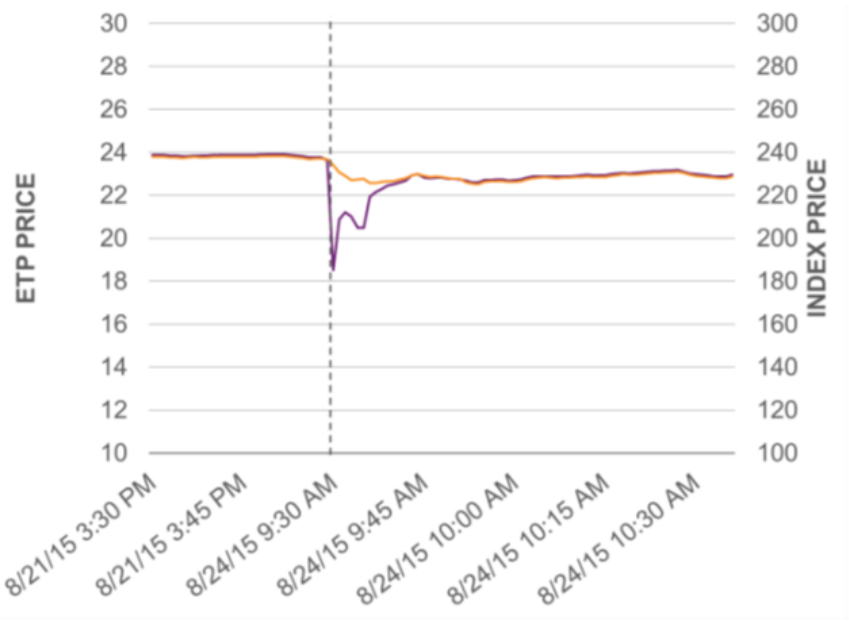


Figure 2: The Proposed Market Illiquidity Measure, MIL

This figure plots the daily (top graph) and monthly (bottom graph) values for the new market illiquidity series, MIL. I estimate MIL based on SPY's high-frequency transaction price data over the period February 1, 2001-December 31, 2019 (see text for details). I report the values in percentages. The highlighted events are: the completion of decimalization in early 2001, the 9/11 attack, the Enron and Gulf War II, the Great Recession, the US debt downgrade of 2011, the Emerging Markets crisis of 2014, the oil price shock of early 2016, the Brexit and the US-China trade war of 2017-2019.

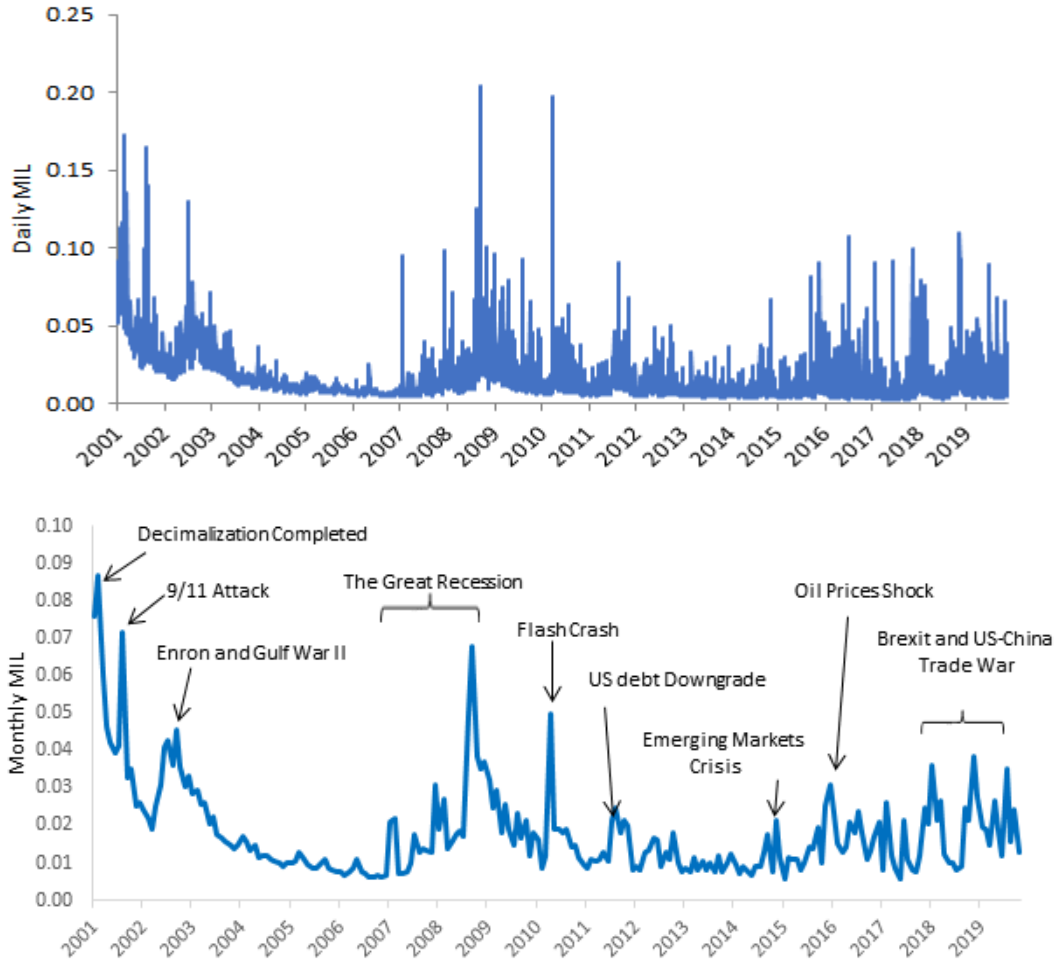


Figure 3: Monthly Market Illiquidity Proxies (in Levels)

This figure plots the longest available illiquidity proxies: the proposed market illiquidity series, MIL (the top continuous line), the Hu, Pan and Wang series, HPW (the top dashed line), the (unscaled) Amihud series, $Amih_un$ (the bottom continuous line line), and the (minus) Pastor Stambaugh liquidity series, PS (the bottom dashed line). Data cover the period February 1, 2001-December 31, 2019. I report the values in percentages.

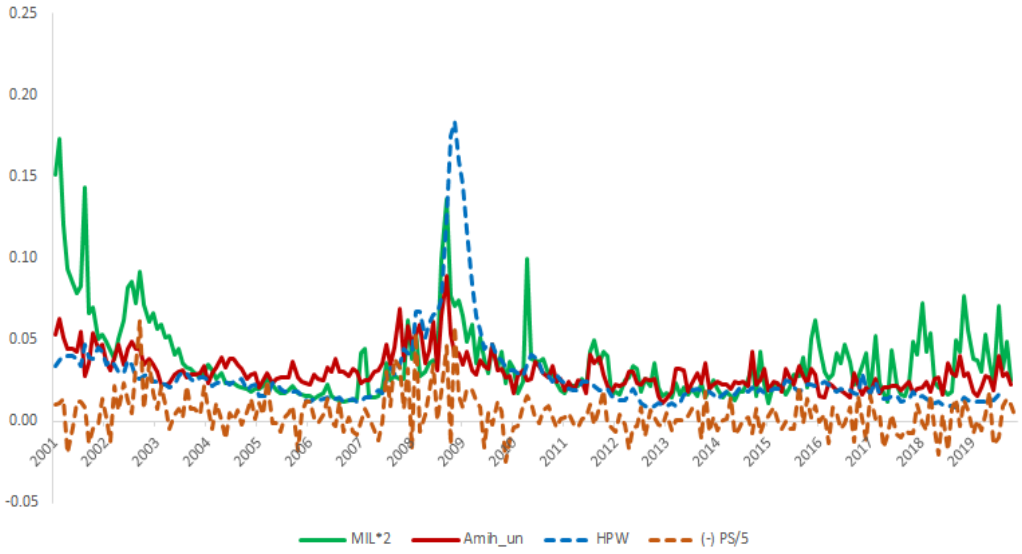


Figure 4: Average Stock Relative Quoted Spreads

This figure plots the daily average stock level relative quoted spread. For each stock, the daily relative quoted spread is defined as $RSpread = (Ask - Bid)/[(Ask + Bid)/2]$. I include in the sample only NYSE listed common stocks (i.e., share code equal to 10 or 11), that trade at least 100 shares per day, every day, during February 1, 2001-December 31, 2019. To keep one tick size regime, the data starts in February 2001 (the last day for the \$1/16 tick-size trading was January 28, 2001 for NYSE-listed securities).

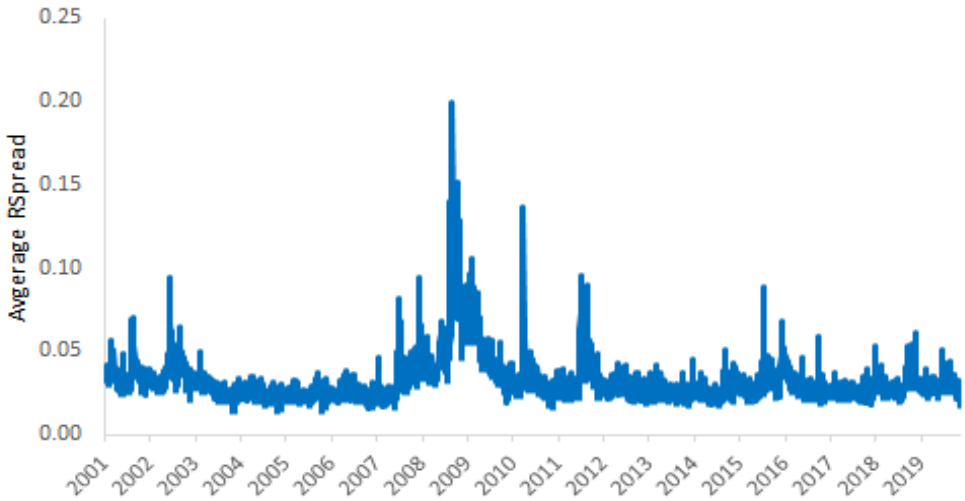


Figure 5: T-statistics for Slope Estimates in Regressions of Stock Illiquidity on Market Illiquidity The graphs below present the distribution of the $T-statistics$ for the slope estimates coming from linear time series regressions, where the daily changes in stock-level relative quoted spread are regressed on the contemporaneous daily changes in market illiquidity. The relative quoted spread is defined as $RSpread = (Ask - Bid)/[(Ask + Bid)/2]$. For market illiquidity I use the new factor, MIL, and the Hu, Pan and Wang (2013) factor, HPW. Data cover the period February 2001 - December 2019. The number of firms equals 2701.

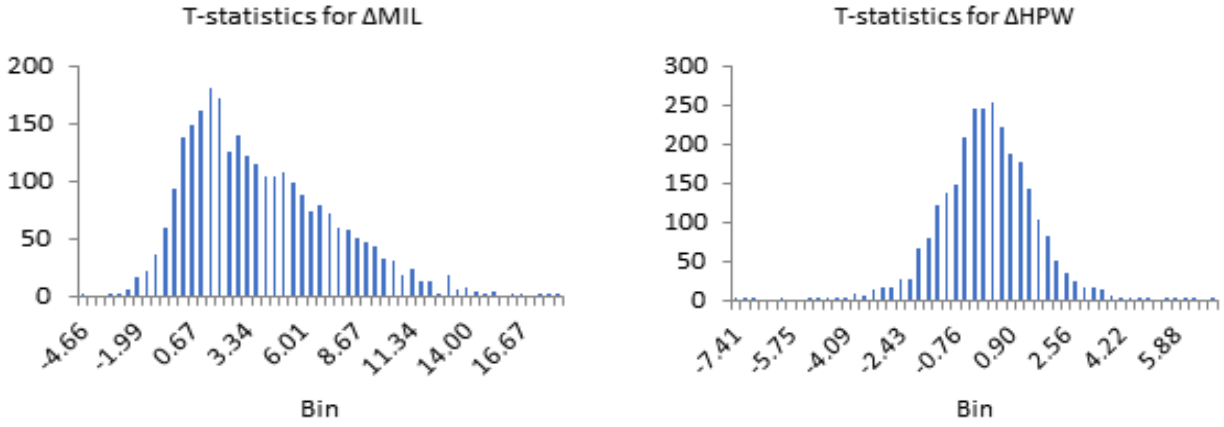


Figure 6: Innovations in MIL

This graph plots the innovations in the monthly market illiquidity, $IMIL$, which is the residual of an $AR(1)$ model applied to the MIL series. Data are reported in percentages and cover the period March 1, 2001-December 31, 2019.

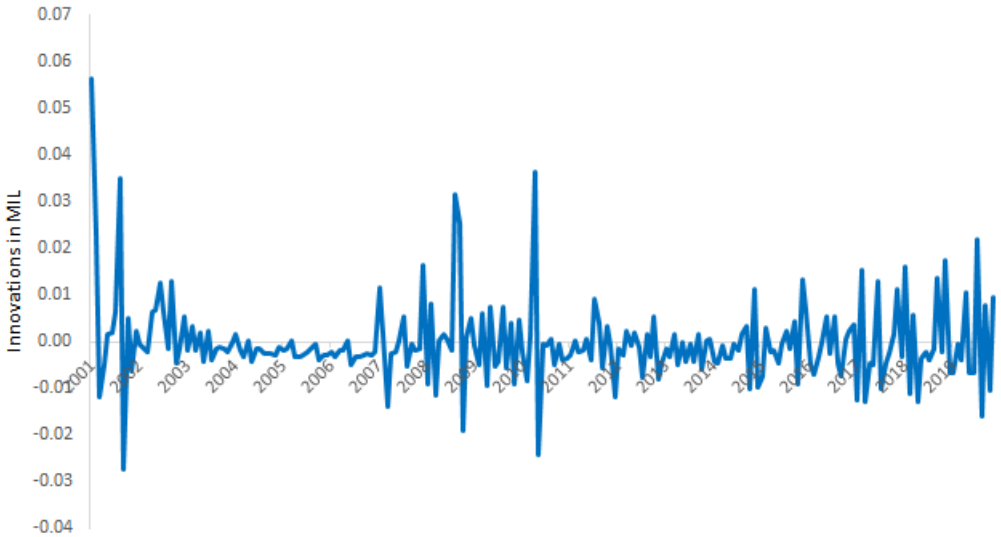
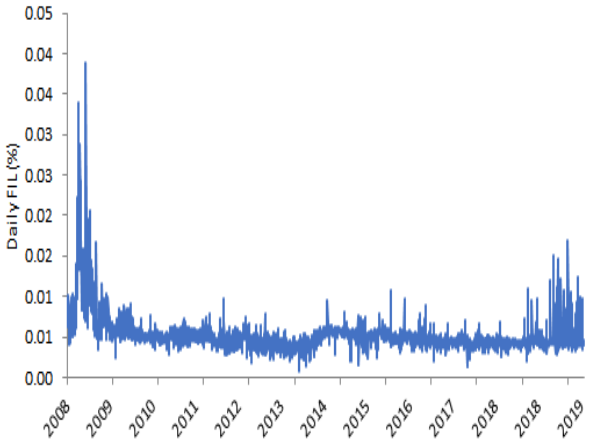


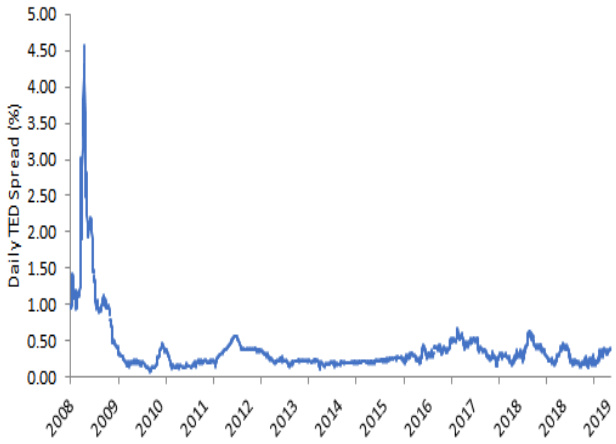
Figure 7: Market Illiquidity and Funding Illiquidity

This graph plots the daily values for the market illiquidity series, MIL, and for the three funding illiquidity proxies: FIL, the $TED\ Spread$, and HPW. The discontinuities in the $TED\ Spread$ graph (total of 75) correspond to U.K. public holidays. The tick marks correspond to the month of July. Data are reported in percentages and cover the period July 2008-December 2019.

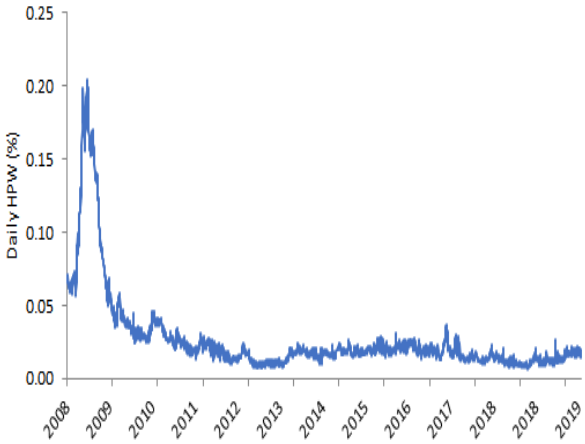
Panel A: First Funding Illiquidity Proxy, *FIL*



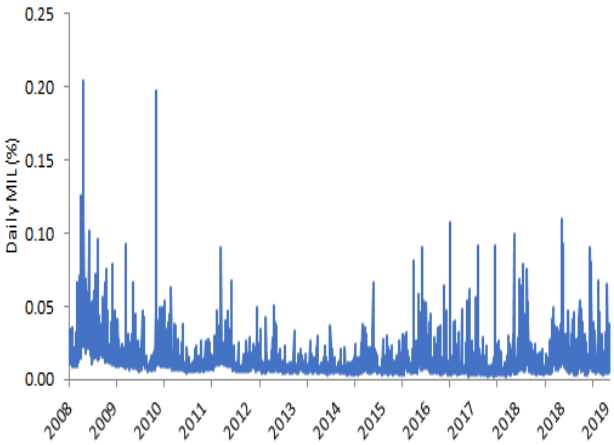
Panel B: Second Funding Illiquidity Proxy, the *TED Spread*



Panel C: Third Funding Illiquidity Proxy, *HPW*



Panel D: Market Illiquidity Proxy, *MIL*



NOT FOR PUBLICATION

Online Appendix: "High-Frequency Arbitrage and Market Illiquidity"

By Claudia E. Moise

A.1 ETFs

This section of the Appendix provides details on exchange traded funds (ETFs) in general, and SPY in particular. ETFs represent a collection or "basket" of securities that tracks a specific market index. ETFs trade on the exchanges like a stock and are priced intra-daily. The main difference between ETFs and other investment vehicles like traditional mutual funds or stocks is the creation/redemption process via which fund shares can be created or redeemed. This process takes place in the primary market between the fund and authorized participants (APs), which are US registered, self-clearing broker/dealers. APs are the only parties who transact directly with the fund and create fund shares in large increments (named creation units, which generally contain 25,000 to 200,000 fund shares) by assembling the underlying securities of the fund with their appropriate weightings. They then deliver these securities to the fund in-kind. In return, APs receive fund shares which are then introduced to the secondary market. There, the shares are traded between buyers and sellers through the exchanges. The APs also have the ability to redeem fund shares, by following the same process in reverse: large increments of fund shares are collected into a redemption unit in the secondary market and then delivered on the primary market to the fund in-kind in exchange for the underlying securities (again, with the appropriate weighting).[1]

The SPY 500 Trust issues and redeems units in multiples of 50,000 units in exchange for S&P500 Index stocks. The SPY is an ETF that, before expenses, corresponds to the price and yield performance of the S&P500 Index. It is used by large institutions and traders either as bets on the overall direction of the market or as a means of passive management. SPY's broker/dealer APs like the new creation units since they bring more fees, and are highly incentivized to move fast in this process. Being highly liquid, and contrary to some individual stocks, SPY shares can be sold short.

Usually, ETFs trade with negligible premiums or discounts, as arbitrage forces will keep them in line with their net asset value (NAV). While the NAV represents the intrinsic value of the ETF shares, the prices of the ETF shares on the market may fluctuate during the trading day. However, spreads between the NAV and the price on the market are usually close due to arbitrageurs that will step in to take advantage of any premiums or discounts to the underlying value by either creating ETF shares and selling them on the market when they trade at a premium, or by redeeming ETF shares and selling the underlying stocks when the ETF shares trade at a discount. For instance, if SPYs traded above their NAV, arbitrageurs would purchase the basket of underlying securities for a lower price and force the fund company to issue new shares. Conversely, if SPYs traded below their NAV, arbitrageurs would buy shares and redeem them for the underlying portfolio of

[1] More details can be found at http://www.indexuniverse.com and http://etfdb.com.

securities.[2]

Figure 1 below displays the time series of the daily SPY dollar trading volume and shares trading volume, for the period February 1, 1993-December 31, 2019. Figure 2 plots the longer daily illiquidity proxies, the *MIL* series and the Hu, Pan and Wang series, over the period February 1, 2001 to December 31, 2019.

[2] See Hill, Nadig and Hougan (2015) for more details on ETFs. See Cherkes et al. (2006) for further discussions and comparisons between ETFs and closed-end funds.

References

[1] Cherkes, M., J. Sagi, and R. Stanton, 2006, A liquidity-based theory of closed-end funds, *Review of Financial Studies* 22, 257–97.

[2] Hill, Joanne M., Dave Nadig, and Matt Hougan, 2015, A comprehensive guide to exchange-traded funds (ETFs), *Research Foundation Books*, 1-181.

Figure 1: Historical Trading Information on SPYs

The top plot displays the time series of the daily SPY dollar trading volume, while the bottom one plots the time series of the daily SPY shares trading volume. I report both series in millions of units for the period February 1, 1993-December 31, 2019.

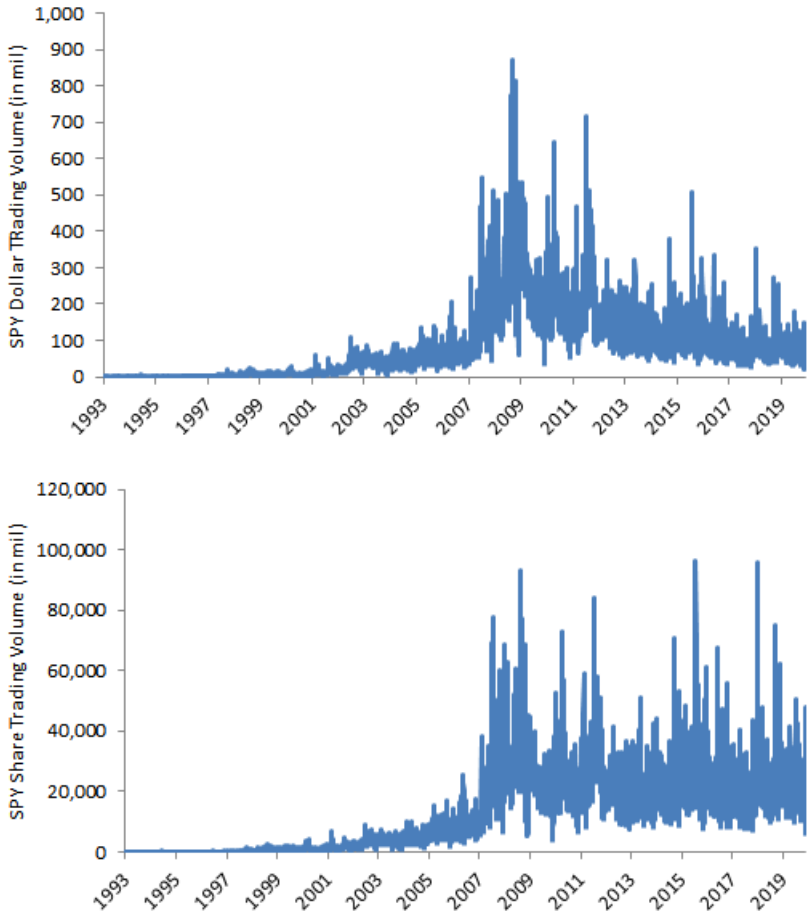


Figure 2: Daily Market Illiquidity Proxies (in Levels)
This figure plots in the top graph the the proposed market illiquidity series, MIL, and in the bottom graph the Hu, Pan and Wang series, HPW. Data cover the period February 1, 2001 to December 31, 2019. I report the values in percentages.

