Liquidity Spillover between ETFs and their Constituents

Abstract

ETF sponsors promote ETFs as having superior liquidity than their constituents because they possess two layers of liquidity- the market liquidity of ETFs and the underlying stocks' liquidity. We find a liquidity connection between the ETF and its underlying stocks, suggesting the potential simultaneous liquidity dry-up in both markets. Liquidity spillovers increase during the market crisis, and economic downturns and are positively related to market volatility and funding constraints. Besides, a stock with high volatility and low trading activity exhibits higher liquidity spillover. Finally, liquidity spillover varies proportionally with ETF arbitrage activity and tends to be lower when short sales constraints exist.

JEL Classification Codes: G11, G23
Keywords: ETFs; Portfolio liquidity; Spillover; Arbitrage; Short Sale Constraints

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1. Introduction

Exchange-traded funds (ETFs) are among the most successful financial innovations of recent decades. As of the fourth quarter of 2022, there was $6.2 trillion in US ETF assets under management and US ETFs accounted for 31.4% of the total US trading volume in the secondary market.[1] The ETF market scale and robust growth give rise to financial stability considerations. One of the main concerns is the ETF market's liquidity risk (e.g., Su, 2018; Pagano, Serrano, and Zechner, 2019; Clements, 2020). This paper documents the magnitude and determinants of liquidity spillover between an ETF and its underlying portfolio. It contributes to addressing a growing concern from investors and regulators about the simultaneous dry-ups of liquidity in financial markets, as shown in the recent market "flash crashes".

Liquidity is a crucial dimension of financial markets. The ability to buy or sell an asset in a timely, low-cost manner influences the pricing of assets and market stability (Amihud and Mendelson, 1986; Lam and Tam, 2011; Bradrania, Peat, and Satchell, 2015). Given its importance, ETF sponsors widely promote ETF as having superior liquidity compared to stock, as J.P. Morgan Asset Management noted that "the reality is that ETF investors often can access significant 'hidden' ETF liquidity beyond what is directly observable in the secondary market."[2]. Thus, ETF provides investors with two layers of liquidity: the liquidity of ETF displayed in the marketplace (i.e., ETF liquidity) and the liquidity of its underlying portfolio (i.e., underlying liquidity)[3]. However, Ben-David, Franzoni, and Moussawi (2018) find that a

[1] Please see, https://www.nasdaq.com/articles/global-etf-market-facts%3A-three-things-to-know-from-q4-2022
[2] J.P. Morgan Asset Management. (2015). Debunking myths about ETF liquidity. Retrieved from: https://am.jpmorgan.com/blob-gim/1383272223898/83456/1323416812894_Debunking-myths-about-ETF-liquidity.pdf
[3] The smooth transition between an ETF's liquidity and its underlying liquidity is proceeded by an "authorized participant" (AP) through the creation/redemption mechanism. The creation occurs when there is a net demand for ETF units in the secondary market. In this case, the AP will buy underlying securities and transfer them to the ETF sponsor in receiving ETF units. These newly issued units will meet the excess demand in the secondary market. Conversely, when there is a net supply of ETF units, the AP will purchase ETF units on the stock exchange and then redeem them with the ETF plan sponsor in exchange for the basket of underlying securities. This

shock to ETF liquidity can propagate to underlying liquidity or vice versa and lead to their simultaneous evaporation of liquidity in both ETF and stock markets during the market crisis. This "liquidity illusion" exposes investors to significant losses and the inability to sell their ETF shares (e.g., Clements, 2020). When selling pressure causes underlying stocks to become illiquid and rapidly lose value, it prompts ETF holders to sell their shares quickly. Market makers and APs would widen their bid-ask spreads to compensate for market volatility and pricing errors. They no longer want to redeem ETF shares and receive in-kind, plummeting, and illiquid securities.[4]. Thus, ETF and underlying liquidity dry up simultaneously, leading to fire sales in both markets (e.g., Su, 2018).

Using daily data of the DIAMONDS ETF on the Dow Jones Industrial Average and its underlying stocks from April 2002 to December 2016, we examine the causality and the magnitude of liquidity spillover between the ETF and its underlying portfolio using a vector autoregressive (VAR) model. Our VAR model considers not only the liquidity spillover effect but also the causal relationship between liquidity and other liquidity determinants such as asset's return or return volatility. We find that the ETF liquidity and its underlying liquidity Granger cause each other, and this causality survives a battery of robustness checks.

In addition, following Diebold and Yilmaz (2012), we compute the pairwise spillover and liquidity spillover index between the ETF and its underlying portfolio. Our results show that the past variation of ETF liquidity is the most critical contributor to the fluctuation of underlying liquidity and vice versa. The average volatility that ETF liquidity receives from underlying liquidity and vice versa is 7.89% using the bid-ask spread as a liquidity measure and 31.12% using Amihud illiquidity as a liquidity proxy. These findings suggest that liquidity

creation/redemption mechanism provides the AP with an arbitrage mechanism to ensure that ETF prices in the secondary market are aligned with the net asset value (NAV) of underlying securities held by the fund sponsor.

[4] APs do not have a legal or fiduciary obligation to create or redeem ETF shares. APs profit by either acting as dealers or market makers in the secondary market, earning the bid-ask spread and profiting off arbitrage opportunities (Clements, 2018). Pan and Zeng (2019) find that ETF arbitrage decreases with a decline in the liquidity of underlying securities.

spillover is significant between ETF and the underlying stock portfolio, implying that ETF liquidity is illusionary.

While past literature on ETFs focuses more on the propagation of shocks from ETFs to underlying stocks (e.g., Krause, Ehsani, and Lien, 2014; Ben-David, Franzoni, and Moussawi, 2018), we find that liquidity shocks from underlying stocks have a more significant effect on ETF liquidity than in reverse. The directional liquidity spillover from underlying liquidity to ETF liquidity is 10.87% using the bid-ask spread and 33.75% using Amihud illiquidity. In contrast, the directional liquidity spillover from ETF to the underlying portfolio is 4.9% using the bid-ask spread and 28.49% using Amihud illiquidity.

Our paper investigates market-level determinants of the liquidity spillover between the ETF and its underlying portfolio. Liquidity spillover shares similar market-level determinants to liquidity commonality. Like the liquidity commonality of stocks documented in Rösch and Kaserer (2014), the liquidity spillover between the ETF and its underlying portfolio is substantially more significant during periods of market crisis, economic slowdown, and high market volatility. These findings are consistent with the "wealth effect" theory of financial contagion of Kyle and Xiong (2002), which argues that increased risk aversion in the marketplace intensifies liquidity spillover among asset classes. The sharp increase in liquidity spillover of bid-ask spread during the global financial crisis (GFC) suggests that market participants and regulators should monitor liquidity dry-ups in the ETF market as they are more pronounced when liquidity is most needed.

Ben-David, Franzoni, and Moussawi (2018) propose that ETF arbitrage is one channel that fuels the transmission of liquidity shocks between ETF and component stocks. Arbitrage depends on costs and capital. They further show that ETFs' effect on underlying volatility is weaker for stocks with higher arbitrage limits and stronger during times of more intense arbitrage activity. Using ETF fund flows and pricing errors as two proxies for ETF arbitrage activity, we find that liquidity spillover varies proportionally with ETF arbitrage activity, consistent with Ben-David, Franzoni, and Moussawi's (2018) proposition.

We also examine the effect of two drivers of ETF arbitrage, namely funding costs and short-sale constraints on liquidity spillover. The effect of funding costs on the liquidity spillover between an ETF and its underlying portfolio is inconclusive in the literature. On the one hand, Ben-David, Franzoni, and Moussawi (2018) find that increased funding costs can lower liquidity spillover by reducing the capital available for ETF arbitrage and raising its opportunity cost. On the other hand, variations in funding costs lead to changes in risk aversion among ETF dealers, which could affect the liquidity transmission between an ETF and its underlying portfolio (e.g., Huberman and Halka, 2000; Kyle and Xiong, 2001; Chordia, Roll, and Subrahmanyam, 2002). We examine the effect of funding costs on liquidity spillover using various funding costs and find their results are different depending on the source of interest rate hikes. An increase in the short-term rate reduces the liquidity spillover, whereas a rise in the default spread increases the liquidity spillover. Furthermore, using a regulatory experiment on short-sale constraints, our difference-in-difference analysis shows that the liquidity spillover between ETF and underlying stocks is negatively correlated with short-sale constraints – a crucial limit to arbitrage. Specifically, we find that the liquidity spillover between the ETF and its component stocks is higher when short-sale restrictions lessen.

Our paper contributes to the literature in several ways. First, our research sheds more light on the liquidity spillover topic, which is still under-researched despite its significance. Liquidity plays a crucial role in the financial market, affecting asset pricing and market stability (e.g., Pastor and Stambaugh, 2003). As a result, the simultaneous dry-up of liquidity between different asset classes or geographic markets is of great interest to market regulators, practitioners, and researchers. This evaporation of liquidity across markets can be caused by the co-movement of liquidity (e.g., liquidity commonality) or the propagation of liquidity shocks (e.g., liquidity spillover) (Cespa and Foucault, 2014). Despite its importance as a cause of liquidity dry-ups, the liquidity spillover from one asset to another asset receives less attention compared to the liquidity commonality (e.g., Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Karolyi, Lee, and Van Dijk, 2012). Our work is driven by the theoretical paper of Cespa and Foucault (2014) on liquidity contagion risk and by the empirical works of Chordia, Sakar, and Subramanyam (2005) and Goyenko and Ukhov (2009) investigating the liquidity spillover between stock and bond markets. They are among the first who directly study the liquidity spillover in financial markets. We expand the empirical analysis of liquidity spillover into ETF and underlying markets and contribute to the literature by providing a direct measure of liquidity spillover and a comprehensive analysis of its determinants.

Second, our paper enriches the literature on ETFs by investigating the magnitude and direction of the liquidity spillover between ETFs and their constituents. While this spillover is expected between an ETF and its underlying portfolio, its intensity and direction are unknown in the literature. Our study is related to the work of Krause, Ehsani, and Lien (2014), who examine the volatility spillover between underlying stocks and ETFs. Our paper, however, is significantly different from theirs in several aspects. First, our paper focuses on liquidity spillover while focusing on volatility spillover. Second, Krause, Ehsani, and Lien (2014) study only the volatility spillover from an ETF to its largest component stocks. By contrast, we provide an entire perspective of the liquidity spillover as we consider the spillover effect of all underlying stocks. Third, our methodology is also different from that of Krause, Ehsani, and Lien (2014) as in our VAR model, we include several endogenous variables that are documented in the literature to influence liquidity such as asset's return and return volatility (e.g., Chordia, Sakar, and Subrahmanyam, 2005; Goyenko and Ukhov, 2009). This approach allows us to simultaneously account for the spillover effect between liquidity, volatility, and return. Additionally, we provide a broader analysis of factors affecting liquidity spillover, including macroeconomic variables and ETF arbitrage activities.

Third, our research contributes to the literature on limits to arbitrage by documenting the effect of arbitrage, funding, and short-sale constraints on the liquidity spillover between ETF and component stocks. Ben-David, Franzoni, and Moussawi (2018) consider the impact of ETF ownership and underlying stock volatility. Our methodologies have some distinct differences from those used by Ben-David, Franzoni, and Moussawi (2018). First, in their paper, the authors document the role of arbitrage as a mechanism that transmits volatility or liquidity shocks from ETF to component stocks by studying the effect of ETF arbitrage and arbitrage costs on component stock volatility. Our paper measures the spillover explicitly between the ETF and its underlying portfolio, thus providing a more direct way to assess the effect of arbitrage activity on spillover. Second, they focus on the spillover effect from ETF to underlying stocks, whereas we consider the spillover effect from both sides. We find evidence that the liquidity spillover from the underlying portfolio to the ETF is more significant than vice versa. Third, Ben-David, Franzoni, and Moussawi (2018) use arbitrage costs (i.e., stock bid-ask spread and lending fees) as limits to arbitrage, while in our paper, we investigate the effect of another limit to arbitrage (i.e., short sale constraints) on spillover. As far as we know, the impact of short-sale restrictions on liquidity spillover between ETF and component stocks is novel, and it has policy implications for financial market regulators. A policy lesson is that stricter short sale regulations such as short sale bans can reduce the liquidity contagion effect between ETF and stock markets and help avoid dry-ups of market liquidity.[5].

Finally, our research directly addresses the growing concern among practitioners, researchers, and market regulators about the "liquidity illusion" risk exposed by the ETF

[5] Our findings give a reason for the usage of a short sale ban during the market crisis. Recently, during the Covid 19- crisis, several countries have prohibited short selling. For instance, Austria, Belgium, France, Greece, Italy, and Spain have banned short selling for some of their domestic stocks from March 18, 2020, to May 18, 2020.

market.[6]. To the best of our knowledge, our present work is the first to investigate this risk's magnitude and evolution over time. We find a significant liquidity spillover between the ETF and its underlying portfolio, especially during periods of economic slowdown. Our results imply that the concern about this risk is pertinent, and market regulators should monitor it during market turbulence.

The remainder of the paper is as follows. Section 2 discusses related literature and develops the hypotheses. In section 3, we describe the data and methodologies used. In section 4, we present the empirical results and discussion. Concluding remarks are provided in section 5.

2. Literature review and development of hypotheses

2.1. Liquidity spillover between ETF and the underlying portfolio

Liquidity spillover between two markets refers to the propagation of liquidity shocks from one market to another and vice versa. Many theoretical models have been proposed in the literature to explain the source of spillover or contagion in financial markets, including liquidity spillover. Kyle and Xiong (2001) suggest the "wealth effect" theory, which attributes liquidity spillover across assets to shocks to financial intermediaries' risk aversion. During a market crisis, loss in one market increases risk aversion and leads them to cut position in other markets. Because of the spillover effect, market depth and liquidity decreased simultaneously in several markets. Kodres and Pritsker (2002) explain financial contagion using the rational expectations model. In their model, contagion exists through cross-market rebalancing, where investors

[6] The flash crash in the US stock market on August 24, 2015, is anecdotal evidence about the disastrous effects of this risk to investors and other market participants. On August 24, 2015, the Dow Jones Industrial Average index experienced one of the largest intraday declines in history. 82 ETFs, including large plain-vanilla index-based ETFs, experienced substantial price swings. More than a dozen ETFs were trading at prices far below the value of their underlying baskets, a phenomenon largely unexpected. Around 40% of all ETPs examined by the SEC declined by more than 10% in value on that day.

transmit idiosyncratic shocks from one market to others by adjusting their portfolio's exposures to common fundamental risks. According to them, the intensity of spillover is a function of markets' sensitivities to common risk factors and information asymmetry in each market. Pasquriello (2007) develops a theoretical model suggesting that heterogeneity of private information in the marketplace can lead to financial contagion.

Cespa and Foucault (2014) develop a theoretical model of cross-asset learning to explain the liquidity spillover between various assets with correlated fundamentals. According to their model, dealers in one asset (e.g., X) use another asset's price (e.g., Y) as a source of information. A liquidity shock to asset Y raises the cost of liquidity provision in this asset and leads to higher uncertainty and liquidity provision cost of the dealer in asset X. Consequently, the decrease in liquidity for asset Y spills to asset X. As an ETF, and its underlying stocks are closely related in term of fundamentals, Cespa and Foucault (2014) use them as a typical example of liquidity spillover through the cross-asset learning process. They further predict that the sensitivity of assets' price informativeness to liquidity shocks and the risk aversion of assets' dealers determine the intensity of liquidity spillover between assets.

Besides the above models, there are many other reasons for the liquidity linkage between an ETF and its underlying portfolio. First, there is a strong volatility connectedness between the two markets, and volatility can affect both markets' liquidity by changing the inventory risk born by market makers (e.g., O'Hara and Oldfield, 1986). As the stock market represents the ETF market's underlying securities, stock market volatility transmits to the ETF market by affecting its net asset value. Second, stock market liquidity can affect ETF market liquidity, a component of ETF market makers' inventory cost. Hill, Nadig, Hougan, and Fuhr (2015) argue that the ETF bid-ask spread depends on the bid-ask spreads of underlying securities. Therefore, a reduction in underlying market liquidity could spill over to ETF market liquidity as it increases ETF market makers' inventory costs.

In reverse, the liquidity spillover could be from ETFs to the underlying portfolio. For instance, Krause, Ehsani, and Lien (2014) document volatility spillover from sector ETFs to their largest component stocks. They argue that shocks to ETF prices driven by liquidity-seeking institutions, noise traders, or industry fundamentals affect their largest component stocks' volatility. Ben-David, Franzoni, and Moussawi (2018) document the arbitrage channel's role in transmitting volatility shocks from ETFs to underlying stocks. Due to their low trading costs, ETFs attract short-horizon liquidity traders and increase the securities' non-fundamental volatility in the baskets through the ETF arbitrage channel. As volatility affects liquidity, this suggests that liquidity can also spill from an ETF over its underlying portfolio.

There is evidence that smaller markets are likely to be more sensitive to transmitted shocks from larger markets (e.g., Wei, Liu, Yang, and Chaung, 1995; Reyes, 2001). For instance, Reyes (2001) uses a bivariate EGARCH model to test for volatility spillover between large- and small-cap stock indexes in the Japanese market. He finds substantial volatility spillover from large-cap stocks to small-cap stocks, but not vice-versa. As the stock market's size is much larger than the ETF market's size, we expect that shocks to the ETF market's liquidity can be better absorbed in the stock market and have less predictive power to predict a change in the stock market liquidity. Furthermore, as a shock to underlying portfolio liquidity directly affects ETF market makers' inventory costs, we expect the magnitude of liquidity spillover from the underlying portfolio to ETF will be greater than that from ETF to the underlying portfolio.

Based on the above discussion, we formulate the first hypothesis as follows.

H1. There is liquidity spillover between an ETF and its underlying portfolio. The magnitude of liquidity spillover from the underlying portfolio to the ETF is more significant than from the ETF to the underlying portfolio.

2.2. Determinants of liquidity spillover

In Kyle and Xiong (2001) and Cespa and Foucault (2014), the intensity of liquidity spillover between two assets depends on the risk aversion of market participants and dealers. In Ben-David, Franzoni, and Moussawi (2018), ETFs and component stocks' volatilities connect through arbitrage activity. High ETF arbitrage activity correlates with the volatility transmitted from ETFs to component stocks. As a result, we expect that market-level and firm-level factors that affect the risk aversion of market participants, including dealers and arbitrage costs, are potential determinants of the intensity of liquidity spillover between an ETF and its underlying portfolio.

2.2.1. Market-level determinants

A stock market crisis or crash is characterized by a sudden dramatic decline of stock prices across a significant cross-section of the stock market, resulting in a considerable loss driven by panic selling due to deteriorating underlying economic or financial factors. The literature documents several pieces of evidence of the heightened spillover effect during the market crisis or economic recession. For instance, Diebold and Yilmaz (2009) find that volatility spillover between equity markets is higher during financial crises. Antonakakis and Vergos (2013) study the spillover of sovereign bond yield in the Eurozone and find spillovers spiked during the US economic recession (2007-2009). Kumar and Prasanna (2018) find that the liquidity spillover between emerging markets and developed markets increased by more than 50% during the financial crisis.

Market decline and market volatility are also important determinants of the risk aversion of liquidity suppliers. In Kyle and Xiong (2001), a liquidity supplier is a convergence trader who takes significant positions in a few assets. When the price of one asset declines, liquidity suppliers suffer trading losses, increasing risk aversion. This reduced capacity for bearing risks leads them to trim their positions in every asset they hold. Shen and Starr (2002) model the role of stock volatility in determining the risk aversion of market makers. They suggest that stock or market volatility correlates with the market makers' risk aversion, and an increase in market volatility could lead to reduced market liquidity. In Brunnermeier and Pedersen (2009), liquidity suppliers usually obtain financing by posting margins or pledging securities that they hold as collateral. When the market declines or market volatility rises, liquidity suppliers risk losing the collateral values and reducing the provision of liquidity, which triggers the selling of many securities in their inventories and reduces their ability to provide liquidity.

Besides, investor sentiment in the stock market could also proxy the market maker's risk tolerance. According to De Long, Shleifer, Summers, and Waldman (1990), the optimism or pessimism sentiments in the market are caused by noise traders. These sentiments generate transitory divergences between the price and intrinsic value of assets. When the average sentiment of noise traders is bearish, noise traders' trading induces price pressure that results in a sealed price lower than the fundamental value (Lee, Jiang, and Indro, 2002). Mispricing can last long under the pressure of market sentiment forces, and this mispricing could affect the market maker's inventory positions and risk aversion. From the market maker's standpoint, Kyle and Xiong (2001) find that under-mispricing associated with a decline in inventory should be more concerned because inventory losses can cause a "wealth effect" and reduce market makers' ability to provide liquidity in the market. Consequently, we expect a bearish investor sentiment that indicates a high risk aversion in the marketplace and intensifies the liquidity spillover between the ETF and its underlying portfolio.

Based on the above discussion, we propose the second hypothesis as follows.

H2. Liquidity spillover between an ETF and its underlying portfolio increases during the economic slowdown. Furthermore, it is positively correlated with the market decline and volatility and negatively correlated with the investor sentiment index's bullishness.

2.2.2. *Effect of ETF arbitrage on liquidity spillover*

Ben-David, Franzoni, and Moussawi (2018) posits that ETF arbitrage is a crucial channel that transmits liquidity shocks from ETFs to component stocks and vice versa. They find that arbitrage costs (e.g., bid-ask spread and lending fee) and arbitrage capital (e.g., hedge funds' trading activity) affect ETF arbitrage activity. They further show that ETFs' effect on volatility is weaker for stocks with higher arbitrage limits and stronger during times of more intense arbitrage activity.

Arbitrage via creation/redemption is a unique feature of ETF that could transmit the volatility and the liquidity from ETFs to underlying portfolios and vice versa. The creation occurs when there is a net demand for ETF units on the secondary market. In this case, the AP will buy underlying securities and transfer them to the ETF sponsor in receiving ETF units. These newly issued units will meet the excess demand in the secondary market. Conversely, when there is a net supply of ETF units, the AP will purchase ETF units on the stock exchange and then redeem them with the ETF plan sponsor in exchange for the basket of underlying securities. This creation/redemption mechanism provides the AP with an arbitrage mechanism to ensure that ETF prices in the secondary market align with the net asset value (NAV) of underlying securities held by the fund sponsor. We expect that the intensity of arbitrage activity of ETF correlates with the liquidity spillover between ETF and the underlying portfolio. As suggested by Ben-David, Franzoni, and Moussawi (2018, P. 2471), "The liquidity shocks can propagate to the underlying securities through the arbitrage channel, and ETFs may increase the nonfundamental volatility of the securities in their baskets."

Funding costs are crucial determinants of arbitrage activity. Rising funding costs could lower the capital available for arbitrage (e.g., Mancini-Griffoli and Ranaldo, 2010) or increase arbitrage capital's opportunity cost (e.g., Neal, 1996). Consequently, rising funding costs in the marketplace could be associated with lower ETF arbitrage. In this direction, increased funding costs reduce liquidity spillover between an ETF and its underlying portfolio. However, funding costs also affect the risk aversion and behavior of liquidity suppliers in the market. In Huberman and Halka (2000), systematic liquidity or market liquidity is dependent on several proxies of funding costs in the marketplace. They find that the bid-ask spread correlates with yield volatility and the daily change in the spread between yields on ten-year and one-year Treasury bonds. Their findings imply that funding costs relate to the risk aversion of liquidity suppliers as market makers adjust bid-ask spread in response to their risk aversion level (e.g., Copeland and Galai, 1983; Glosten and Harris, 1988). Chordia, Roll, and Subrahmanyam (2002) use the daily first difference in the Federal Funds Rate as a proxy of dealers' funding cost. They find that trading activity measured by the number of trades inversely relates to this proxy.

Besides funding costs, Shleifer and Vishny (1997) suggest that short-sale constraints are an essential source of limited arbitrage in the financial market and lead to asset mispricing persist. Since then, short selling on the limit of arbitrage occurs in several markets. For instance, Engelberg, Reed, and Ringgenberg (2012) find that stocks with more short-selling constraints have lower returns and less price efficiency. Ofek, Richardson, and Whitelaw (2004) find that short-sale restrictions are associated with violations of put-call parity in the options market. Fung and Draper (1999), and Gay and Jung (1999) find that short-sale limitations are the source of mispricing in the futures market, limiting index arbitrage activity. We expect short-sale constraints could affect their liquidity spillover by affecting arbitrage activity between ETFs and component stocks.

Based on the above discussion, we formulate our third hypothesis as follows:

H3. Liquidity spillover between an ETF and its underlying portfolio increases with the intensity of arbitrage activity. The effect of funding costs on liquidity spillover between an ETF and its underlying portfolio is uncertain. At the same time, short sale constraints reduce liquidity spillover between an ETF and its component stocks.

3. Data and liquidity spillover estimation

3.1. Data

We use the DIAMONDS ETF and its component stocks as our study's scope, with the research period from April 1, 2002, to December 31, 2016. The DIAMONDS ETF was launched in 1998 and is managed by State Street Global Advisors. The ETF's underlying index is the Dow Jones Industrial Average, the oldest stock index in the US market tracking thirty large, publicly owned blue-chip companies trading on the New York Stock Exchange and the NASDAQ. As of December 2016, the DIAMONDS ETF has assets under management of USD 14.83 billion, making it one of the largest ETFs listed in US markets. Given its importance, DIAMONDS ETF has been used in several ETF studies such as Hegde and McDermott (2004), Alexander and Barbosa (2008), and Ivanov (2013). The long history of the DIAMONDS ETF allows us to observe the liquidity spillover between ETF and the underlying portfolio over a long time, which covers the Global Financial Crisis. Furthermore, its longevity also permits us to investigate the impact of short-sales constraints on liquidity spillover by employing a regulatory experiment on July 28, 2004. Daily data on trading characteristics of the DIAMONDS ETF and its component stocks are from the CRSP database. Daily holding data of the ETF come from Morningstar. The ETF's net asset value (NAV) over time is from Bloomberg. The final list of component stocks includes 44 blue chips between 2002 and 2016.

Our paper uses a wide range of macroeconomic data from various sources. Data about funding costs such as Fed Fund Rates, yields on a 10-year government bond, and yields on Moody's Baa corporate bond are available online on the website of the Federal Reserve Bank of St. Louis[7]. Data on the put-call ratio and the CBOE Volatility Index (VIX) are from the database of the Chicago Board Options Exchange[8] (CBOE). Data on the investor sentiment index, the high-low ratio, comes from barchart.com. We gather data on the monthly United States Purchasing Managers Index (PMI) on the DataStream for economic activity.

Our paper uses a regulatory experiment to investigate the impact of short-sale restrictions on liquidity spillover. This regulatory experiment is the Regulation SHO pilot program, designated to remove short-sale constraints for randomly selected stocks listed in US markets from May 2, 2005, to August 6, 2007. The list of pilot securities is collected online via the Securities and Exchange Commission (SEC)[9].

3.2. Methodology

3.2.1. Liquidity proxies

Our paper uses two popular proxies to measure the liquidity of the ETF and its underlying stocks. The first proxy is the daily quoted bid-ask spread (QSPR). According to Chung and Zhang (2014), the QSPR is a good estimation of liquidity as it is highly correlated with the intraday bid-ask spread, which is often used to measure the true liquidity of an asset. The QSPR is estimated as follows,

$$QSPR_{i,d} = 100\% \times 2 \times (ASK_{i,d} - BID_{i,d})/(ASK_{i,d} + BID_{i,d}) \quad (1)$$

where $ASK_{i,d}$, and $BID_{i,d}$ are quoted ask and bid prices of the ETF or stock i on day d.

The second proxy is the Amihud (2002) illiquidity ratio ($Amihud$), which is calculated as:

[7] https://fred.stlouisfed.org/
[8] http://www.cboe.com/data/historical-options-data/volume-put-call-ratios
[9] https://www.sec.gov/spotlight/shopilot.htm.

$$Amihud_{i,d} = 10^6 \times |R_{i,d}|/V_{i,d} \quad (2)$$

where $R_{i,d}$ and $V_{i,d}$ are the return and dollar volume on day d of stock i or the ETF. This measure of liquidity gives the absolute percentage price change per dollar of trading volume, or the price impact of order flow of that day. The larger the Amihud measure, the more illiquid the security.[10]

3.2.2. Diebold and Yilmaz's (2012) spillover index

Our paper's key variable of interest is the liquidity spillover between the ETF and its underlying portfolio. This variable is computed based on Diebold and Yilmaz's (2012) volatility spillover index. We use this section to review their methodology. Suppose that we have an *N*-variable p-lags VAR (*p*) model as follows:

$$x_t = \sum_{i=1}^{p} \Phi_i \, x_{t-i} + \varepsilon_t \quad (3)$$

where $\varepsilon \sim (0, \boldsymbol{\Sigma})$ is a vector of independently and identically distributed disturbances; x_t is a vector of variables including the ETF liquidity and its underlying liquidity. Using a moving average representation, Eq. (3) becomes:

$$x_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i} \quad (4)$$

where the NxN coefficient matrices A_i follow the recursion

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p} \quad (5)$$

with A_0 being an $N \times N$ identity matrix with $A_i = 0$ for $i < 0$. The moving average coefficients are used to construct the variance decompositions. Diebold and Yilmaz (2012) use the generalized VAR framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998),

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[10] As per Eq. (2), we scale the Amihud illiquidity by 10^6, making it the price impact of a million-dollar volume.

referred to as KPPS, to compute the fraction of the H-step-ahead error variance in forecasting x_i that is due to shocks to x_j, $\forall\, j \neq i$. Each variable H-step-ahead variance decomposition is denoted by $\tilde{\theta}_{ij}^{g}(H)$, for $H = 1,2,3, \ldots$, and is computed as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} e_i' A_h \Sigma A_h' e_i} \tag{6}$$

where Σ is the variance matrix for the error vector ε. σ_{jj} is the standard deviation of the error term for the jth equation, and e_i is the selection vector, with one for the ith element and zero otherwise. Each entry of the variance decomposition matrix is normalized as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

Each entry is a pairwise spillover between two variables in the VAR system. For instance, the normalized entry in Eq. (5) is the pairwise spillover index from variable j to variable i, indicating how much variation in percentage variable i receives from variable j given its total variation of 100%. Note that, by construction, $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. The formula gives the total spillover index:

$$S^{g}(H) = \frac{\sum_{i,j=1; i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} . 100 \tag{8}$$

Diebold and Yilmaz (2012) also calculate the direction spillover index to gauge the spillover received by variable i from all other variables j and vice versa. The directional spillover index received by variable i from all other variables j is:

$$S_{i.}^{g}(H) = \frac{\sum_{j=1; i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} . 100 \tag{9}$$

In reverse, the directional spillover index transmitted by variable i to all other variables j is:

$$S_{.i}^{g}(H) = \frac{\sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{ji}^{g}(H)}{N}.100 \tag{10}$$

The net spillover from variable i to all other variables j is the difference between the gross volatility shocks transmitted to and those received from all other variables as:

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H) \tag{11}$$

3.2.3. Liquidity spillover index

To apply the connectedness framework of Diebold and Yilmaz (2012), we propose a vector autoregressive (VAR) system that includes liquidity, return, and volatility of the ETF and its underlying portfolio. The inclusion of return and volatility is based on the extant literature that has documented significant impacts of volatility and return on liquidity (e.g., Amihud and Mendelson, 1986; Datar et al., 1998; Stoll, 2000; Jun et al., 2003; Hameed et al., 2010). Based on Chordia, Sakar, and Subramanyam (2005) and Goyenko and Ukhov (2009), we specify Eq. (3) by using the following vector autoregressive (VAR) model to study the lead-lag relationship between the ETF liquidity and the liquidity of its underlying portfolio:

$$X_t = \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + \varepsilon_t \tag{12}$$

$$Y_t = \sum_{j=1}^{k} \mu_j Y_{t-j} + \sum_{j=1}^{k} \lambda_j X_{t-j} + \phi_t \tag{13}$$

where X and Y are vectors representing daily values of liquidity, return, and volatility of the ETF and the underlying portfolio, respectively. The above VAR system includes a 6-equation vector autoregression specification that incorporates six variables: three for the ETF (liquidity: $LIQ_{E,t}$, return: $RET_{E,t}$, and volatility: $VOL_{E,t}$) and three for the underlying portfolio (liquidity:

$LIQ_{U,t}$, return: $RET_{U,t}$, and volatility: $VOL_{U,t}$). Liquidity can be proxied by either the quoted bid-ask spread or the Amihud illiquidity ratio described in Eqs. (1) and (2). We use daily high and low prices to compute Parkison's (1980)[11] daily stock and ETF volatilities:

$$VOL_t = \sqrt{0.361} * (\log(High_t) - \log(Low_t)) \tag{14}$$

where VOL_t is a stock or the ETF volatility on day t; $High_t$ and Low_t are the high and price low prices of the stock or the ETF on day t.

Each variable of the underlying portfolio is the weighted average of the variable across all portfolio stocks. The weights are the holding percentages of stocks in the ETF. Since the underlying index of the ETF (i.e., the Dow Jones Industrial Average) is price-weighted, the stock weights in the underlying portfolio are based on their prices rather than their market capitalization. We apply seasonality and deterministic variations adjustment following Gallant, Rossi, and Tauchen (1992). The number of lags, *k*, in Eqs. (12) and (13) are chosen based on Akaike information criteria (AIC).

We create a new measure, the *Liquidity Spillover Index* measuring the average liquidity spillover that the ETF receives from its underlying portfolio and vice versa. The average value of pairwise spillovers between the ETF liquidity and the underlying liquidity is calculated using Diebold and Yilmaz's (2012) methodology described earlier. The equation of the *Liquidity Spillover Index* is:

$$LSI = \frac{\left(\tilde{\theta}^{g}_{ETF,Under} + \tilde{\theta}^{g}_{Under,ETF}\right)}{2} \tag{15}$$

where *LSI* is the *Liquidity Spillover Index* between the ETF and its underlying portfolio; $\tilde{\theta}^{g}_{ETF,Under}$ is the pairwise spillover from the underlying liquidity to the ETF liquidity;

[11] This measure of daily stock volatility is widely used in literature (e.g., Alizadeh, Brandt, and Diebold (2002); Chan and Lien (2003); Diebold and Yilmaz (2012), and Krause, Ehsani, and Lien (2014)).

$\tilde{\theta}^{g}_{Under,ETF}$ is the pairwise spillover from the ETF liquidity to its underlying liquidity. $\tilde{\theta}^{g}_{ETF,Under}$, and $\tilde{\theta}^{g}_{Under,ETF}$ are calculated from Eq. (7).

3.2.4. Main regression equations

To investigate the determinants of liquidity spillover between the ETF and its underlying liquidity, we first construct a non-overlapped time series of the *Weekly Liquidity Spillover Index* ($WLSI$), the difference between the rolling LSI using a 205-day window and the 5-day lagged value of the rolling LSI using a 200-day window[12]. Then we regress the following equation:

$$WLSI_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \tag{16}$$

where $WLSI_k$ is the *Weekly Liquidity Spillover Index* between the ETF and its underlying portfolio using either the bid-ask spread or the Amihud illiquidity ratio in week k. $Controls_{k-1}$ is a set of control variables in week $(k-1)$, including ETF_CAP_{k-1} and ETF_VOLUME_{k-1}, with ETF_CAP_{k-1} being the logarithm of the weekly average market capitalization of the ETF measured in USD million and ETF_VOLUME_{k-1} being the logarithm of weekly average trading volume of the ETF measured in thousands of shares. $Interests_{k-1}$ is a set of variables of interest in week $(k-1)$ and ε_k is the error term.

We are also interested in examining the drivers of directional liquidity spillover between the ETF and its underlying liquidity. Therefore, we construct a non-overlapped time series of *Weekly Directional Liquidity Spillover Index* ($WDLSI$), which is the difference between the rolling pairwise spillover between the ETF liquidity and its underlying liquidity using a 205-day window and the 5-day lagged value of the rolling pairwise spillover between

[12] The 200-day window is used to calculate the rolling total spillover index in Diebold and Yilmaz (2012) and Krause, Ehsani, and Lien (2014).

the ETF liquidity and its underlying liquidity using 200-day window. As the pairwise spillover indicates the directional spillover between the ETF and its underlying portfolio, we will have two *DLSIs*, one from the ETF to its underlying portfolio ($WDLSI_{ETF \rightarrow Underlying}$) and one from the underlying portfolio to the ETF ($WDLSI_{Underlying \rightarrow ETF}$). Determinants of *WDLSI* are examined through the following regression:

$$WDLSI_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \tag{17}$$

where $WDLSI_k$ is a *Weekly Directional Liquidity Spillover Index* between the ETF and its underlying portfolio using either the bid-ask spread or Amihud illiquidity ratio. $Controls_{k-1}$ and $Interests_{k-1}$ in Eq. (17) are the same as Eq. (16).

4. Empirical results

4.1. Magnitude and direction of liquidity spillover

4.1.1. Descriptive statistics and diagnostic tests

In Table 1 Panel A, we report the descriptive statistics of variables in Eqs. (12) and (13) and their diagnostic tests. The ETF bid-ask spread ($QSPR_E$) mean value is 0.013%, much lower than the mean value of the underlying bid-ask spread ($QSPR_U$) of 0.054%. Similarly, the DIAMONDS ETF has a lower Amihud illiquidity ratio than its underlying portfolio. These findings imply that compared to its underlying portfolio, the DIAMONDS ETF is more liquid, consistent with Marshall, Nguyen, and Visaltanachoti (2018). The time series of liquidity measures of both the ETF and its underlying portfolio is plotted in Appendix A1, showing that the DIAMONDS ETF has greater liquidity than its portfolio most of the time. We report the Ljung-Box Q-statistic, which examines the null hypothesis that there is no autocorrelation. We estimate the Q-statistic for lag lengths of 1, 5, and 20, and we can reject the null of no autocorrelation at the 1% level for all variables in the VAR model in all cases.

As the VAR model requires that its variables be stationary, we conduct two tests for the stationarity of the variables and report the results in Table 1 Panel B. The first is the Augmented Dickey-Fuller test (ADF), and the second is the Phillips-Perron test (PP). From the results of both tests, we can reject the null hypothesis that there is a unit root in the time series. In other words, these variables are stationary and suitable as inputs for the VAR model.

In Table 1 Panel C, we present the correlation matrix of variables in the VAR model. As the ETF tracks its underlying portfolio, a strong positive contemporary correlation (0.986) between the ETF return and its underlying portfolio return. The correlation coefficients between liquidity measures of the ETF and its underlying portfolio are also significantly positive. The correlation between ETF and the underlying bid-ask spread is 0.68, whereas Amihud's illiquidity is 0.742.

[Please insert Table 1 about here]

4.1.2. Granger causality test

We use Granger causality to discern a lead-lag relationship between the ETF and its underlying liquidity. Table 2 reports the pairwise Granger causality tests for each pair of the variables in Eqs. (12) and (13). For each pair, there are two tests. For example, for the pair of the ETF bid-ask spread, $QSPR_E$, and the underlying bid-ask spread, $QSPR_U$, the null hypothesis of Test 1 is that $QSPR_E$ is influenced by itself, not $QSPR_U$. The null hypothesis of Test 2 is that $QSPR_U$ is influenced by itself but not $QSPR_E$. The Granger test results in Table 2 show strong bi-directional causality between the ETF liquidity and its underlying liquidity. The Chi-square statistics for Test 1 and Test 2 for the pair of $QSPR_E$ and $QSPR_U$ are 254.3 and 55.6, respectively. They are both statistically significant (*p-value* < 0.0001), implying that ETF bid-ask spread can be predicted by past values of the underlying bid-ask spread and vice versa. The bi-directional causality also holds for the ETF and its underlying Amihud illiquidity ratio. The Chi-square statistics for Test 1 and Test 2 of this pair are significant, with 45.61 and 48.44, respectively.

[Please insert Table 2 about here]

As robustness tests, we conduct several modifications of the VAR model in Eqs. (12) and (13). First, we proceed with the VAR model at the stock level instead of the portfolio level. We report the Granger causality tests for each component stock with the ETF in Appendix A2. In Test 1, the null hypothesis is that the ETF liquidity is influenced by itself but not underlying stock liquidity. Test 2's null hypothesis is that the underlying stock liquidity is influenced by itself but not ETF liquidity. Test 1 indicates that ETF liquidity Granger causes stock liquidity for 37 out of 43 component stocks using the bid-ask spread as a liquidity proxy. This ratio is 32/43 when using Amihud as a liquidity proxy. Test 2 also confirms the bi-directional relationship between ETF and underlying liquidity. They show that the bid-ask spread of 39 stocks Granger causes ETF while the Amihud ratio of 32 stocks Granger causes the ETF's Amihud illiquidity. Overall, the results are consistent with Table 2 about the bi-directional causality between ETF and its underlying liquidity using the VAR model at the portfolio level.

Second, we include two exogenous variables in Eqs. (12) and (13) and re-conduct the Granger causality tests. Based on Stoll (2000), we choose the market risk measured by the CBOE VIX and the market turnover measured by the dollar volume in USD million of the S&P 500 index as exogenous variables. The results of the Granger causality test for the VAR model with exogenous variables are shown in Appendix A3. We find that ETF liquidity Granger causes underlying liquidity and vice versa, which is consistent with the findings in the VAR model without exogenous variables. The results are robust for both liquidity measures - bid-ask spread and Amihud illiquidity ratio.

Third, we use a third illiquidity measure, the modified Amihud illiquidity suggested by Florackis, Gregoriou, and Kostakis (2011) for our VAR model in Eqs. (12) and (13). The modified Amihud illiquidity ratio is strongly related to the Amihud illiquidity. The correlation coefficient between the modified Amihud and the Amihud illiquidity is 0.84 for the ETF and 0.93 for the underlying portfolio. The results of the Granger causality test using the modified Amihud illiquidity are presented in Appendix A4. These results confirm those in Table 2.

4.1.3. Liquidity spillover results

To compute the liquidity spillover between the DIAMONDS ETF and its underlying portfolio, we use the framework to calculate the volatility spillover index proposed by Diebold and Yilmaz (2012) and the equations of the VAR model in Eqs. (12) and (13), as presented in Section 3.2.2. We use generalized variance decompositions of 10-day-ahead volatility forecast errors. The spillover table between variables in Eqs. (12) and (13) are presented in Table 3. We construct Panels A and B of Table 3 using the bid-ask spread and Amihud illiquidity ratio as liquidity proxies, respectively.

[Please insert Table 3 about here]

In Table 3, the diagonal value represents the spillover of its variable. The off-diagonal elements for each column represent pairwise spillover to other variables, and the off-diagonal elements for each row represent pairwise spillover received from other variables. Pairwise spillover indicates how a shock causes many variations in the row variable's forecast error to the column variable. *The other* column is the sum of all off-diagonal values in the same row, measuring the proportion of forecasted error variance of a row variable explained by shocks to other variables in the VAR system. *The other* row is the sum of off-diagonal values in the same column, measuring the column variable's total volatility to other variables in the model. *Net spillover* is calculated as the difference between contributions *To others* and *From others* for each variable in the table. *Spillover Index* measures the average volatility that one variable receives from other variables in the system.

For instance, we find that 10.87% of the forecasted error variance of the ETF bid-ask spread, $QSPR_E$ in the first row of Panel A, is due to shocks to the underlying bid-ask spread, $QSPR_U$ in the fifth column. This is about the same as the total spillover that $QSPR_E$ receives from other variables: VOL_E (2.64%), RET_E (2.36%), VOL_U (3.05%), and RET_U (2.32%). On the contrary, in the second column, shocks to the ETF bid-ask spread, $QSPR_E$ explains only 4.9% of the variation in forecast error of the underlying bid-ask spread, $QSPR_U$ in the fourth row. This represents a third of the 15.38% total spillover that $QSPR_U$ receives from all off-diagonal variables. The *To others* value of $QSPR_E$ is 7.11% indicating that its shock contributes 7.11% to the variations in forecast errors of other variables in the system: VOL_E (0.38%), RET_E (0.65%), $QSPR_U$ (4.9%), VOL_U (0.46%), and RET_U (0.71%). The *Net spillover* of $QSPR_E$ (-14.13%) equals its contributions to others (7.11%) minus its receipts from others (21.24%). It implies that $QSPR_E$ is a net receiver of volatility. The *Liquidity Spillover Index* of 7.89% is the average pairwise spillover from the underlying liquidity to the ETF liquidity (10.87%) and the pairwise spillover index from the ETF liquidity to its underlying liquidity (4.90%).

In Table 3 Panel B, the pairwise spillovers from the underlying Amihud to the ETF Amihud and vice versa are 33.7% and 28.49%, respectively. The *Liquidity Spillover Index* between them is 31.12%, significantly higher than the bid-ask spread spillover. Overall, the results in Table 3 convey three important messages regarding Hypothesis 1 proposed in Section 2.1. First, the liquidity spillover exists between the DIAMONDS ETF and its underlying portfolio. Second, among other variables in the model except for its past liquidity, shocks to the underlying liquidity are the most crucial driver of forecast error variance of the ETF liquidity. The reverse is also true: shocks to the ETF liquidity are most important in explaining the underlying portfolio's forecast error variation. Third, the effect of shocks from its underlying liquidity to the ETF liquidity is larger than the impact of shocks from the ETF liquidity to its underlying liquidity, consistent with our expectations. The above remarks are similar for both models using either bid-ask spread or Amihud illiquidity ratio as a liquidity proxy.

4.2. Market-level determinants of liquidity spillover

This section investigates the impact of several market-level factors on liquidity spillover between the DIAMONDS ETF and its underlying portfolio, as suggested in Hypotheses 2 and 3. Figure 1 plots the rolling LSI using a 200-day window over the research period 2002-2016 using either spread or Amihud as liquidity proxy. The figure shows that the LSI using the Amihud illiquidity ratio is more volatile than the LSI using the bid-ask spread, and it has increased to nearly 50% during the GFC period (2017-2019). The $WLSI$ time series using the spread and Amihud illiquidity ratio are in Figure 2.

[Please insert Figure 2 about here]

As in Hypothesis 2, we expect that liquidity spillover between the DIAMONDS ETF and its underlying portfolio will increase during an economic recession or financial crisis. These economic stages are characterized by a declining stock market, lower economic activity, and greater stock volatility. All these factors increase the risk aversion of market makers in ETF and underlying stock markets. Additionally, we forecast that liquidity spillover between the ETF and its underlying portfolio is higher when the market declines and exhibits greater volatility. Finally, the liquidity spillover negatively correlates with the bullishness of the investor sentiment index.

To investigate the impact of these market factors on the liquidity spillover between the DIAMONDS ETF and its underlying portfolio, we regress Eqs. (16) and (17) with five macro-level variables of interest. First, we use the United States Purchasing Managers Index (PMI) pioneered by IHS Markit[13] as a proxy for the US economic activity. The index varies between 0 and 100, with a reading above 50 indicating an overall increase in economic activity compared to the previous month and below 50 for an overall decrease. Our dummy variable for economic activity, PMI_D_{k-1} has a value of 0 if the PMI in week $(k-1)$ is below or equal to 50 and 1 if the PMI is higher than 50. To proxy for the market conditions, we use MKT_RET_{k-1}, the market return of the S&P 500 index in week $(k-1)$, and MKT_STD_{k-1}, the market volatility measured as the standard deviation of market returns for five consecutive trading days in week $(k-1)$.

We use two market sentiment indexes frequently used in the literature and investment industry to assess market sentiment impact on the liquidity spillover between the DIAMONDS ETF and its underlying portfolio. The first sentiment index is the put-call ratio (PCR_{k-1}) of stocks listed on the New York Stock Exchange (NYSE) computed daily by the Chicago Board Options Exchange (CBOE). The PCR is a ratio of put volume divided by call volume. Intuitively, this is the ratio of investors betting on the decrease in stock price versus investors betting on the increase. This measure captures investor sentiment (e.g., Dennis and Mayhew, 2002; Guo, 2004; Bandopadhyaya and Jones, 2008). A high level of PCR indicates that the market sentiment is bearish, whereas a low level of PCR signals that the market mood is bullish. In addition to the PCR, we use another market sentiment index: the high-low index (HLR_{k-1}) of the S&P 500. This index compares the number of component stocks of the S&P 500 that

[13] For more details about the construction of the index, see https://ihsmarkit.com/products/pmi.html.

make up 52-week highs instead of the number of component stocks making up 52-week lows. When the index is at a high level, it signals bullish market sentiment and vice versa.

The regression results of Eqs. (16) and (17) using the above variables of interest are presented in Table 4. We report results using the bid-ask spread and Amihud as liquidity proxies in Panel A and Panel B. We use the $WLSI$ as the dependent variable for model specifications (1), (2), and (3); the $WDLSI_{ETF\rightarrow Underlying}$ as the dependent variable for model specifications (4), (5), and (6); the $WDLSI_{Underlying\rightarrow ETF}$ as the dependent variable for model specifications (7), (8), and (9). Consistent with our expectation in Hypothesis 2 that liquidity spillover increases when the economic activity is slowing down, the coefficient of PMI_D_{k-1} is negative and significant in model specifications (1), (2), and (3) in Panel A. This suggests that when economic activity decreases, the liquidity spillover increases. Our findings of the evolvement of liquidity spillover during periods of lower economic activities are consistent with the evidence of volatility spillover (e.g., Diebold and Yilmaz, 2012) or liquidity commonality (e.g., Rösch and Kaserer, 2014). In Panel B, we find that the negative relationship between liquidity spillover and economic activity holds when liquidity is proxied by the Amihud ratio. An economic slowdown does not affect the bid-ask liquidity spillover from the ETF to its underlying portfolio ($WDLSI_{ETF\rightarrow Underlying}$), as shown in model specifications (4), (5), and (6) in Panel A, and the liquidity spillover from the underlying portfolio to the ETF ($WDLSI_{Underlying\rightarrow ETF}$), as shown in model specifications (7), (8), and (9). However, in Panel B, we reveal that both the liquidity spillover from the ETF to its underlying portfolio ($WDLSI_{ETF\rightarrow Underlying}$) and that from the underlying portfolio to the ETF ($WDLSI_{Underlying\rightarrow ETF}$) tend to increase when economic activity is slower.

The coefficient of market return, MKT_RET_t is insignificant for all model specifications in Panel A and Panel B. On the contrary, the effect of market volatility on liquidity spillover exists and is robust as the coefficient of MTK_STD_t is significantly positive for all regression models using *WLSI* as the dependent variable. The positive sign of the coefficients of MTK_STD_t indicates that liquidity spillover is higher during a volatile market, which is in line with our expectation in Hypothesis 2. In Panel A, the effect of market volatility on liquidity spillover from the ETF to its underlying portfolio ($WDLSI_{ETF \rightarrow Underlying}$) is muted as shown in model specifications (4), (5), and (6), whereas the liquidity spillover from the underlying portfolio to the ETF ($WDLSI_{Underlying \rightarrow ETF}$) is positively correlated with market volatility as in columns (7), (8), and (9). Besides, in Panel B, the impact of market volatility on both $WDLSI_{ETF \rightarrow Underlying}$ and $WDLSI_{Underlying \rightarrow ETF}$ is positive and highly significant. This indicates that market volatility intensifies the transmission of price impact shocks from the ETF to its constituent stocks and vice versa.

We find that market sentiment indexes do not affect liquidity spillover using the bid-ask spread as a liquidity proxy. However, when the Amihud illiquidity ratio is used, the results show that the market sentiment index measured by either PCR_{k-1} or HLR_{k-1} affects liquidity spillover in tandem with our expectations. Specifically, the coefficient of PCR_{k-1} in columns (1) and (3) is significantly positive, implying that when the market is bearish (i.e., PCR is high), the liquidity spillover between the ETF and its underlying portfolio tends to be higher. In a similar vein, the estimated parameter of HLR_{k-1} is columns (2) and (3) is significantly negative, indicating that the stock market bearishness (i.e., HLR is low) increases the transmission of liquidity shocks. Further results in columns (4) to (9) of Panel B show that the market sentiment indexes exhibit a significant effect on both the liquidity spillover from the ETF to its underlying stocks and vice versa.

[Please insert Table 4 about here]

In summary, we find intriguing results about the heterogeneous effects of market conditions on the spillover between the ETF and its underlying liquidity. Specifically, market volatility would increase the spillover from the underlying spread to ETF spread. Simultaneously, this factor does not affect the spillover from the ETF spread to the underlying spread. The market return does not influence the directional liquidity spillover between the ETF and its underlying portfolio, as its coefficient is insignificant for all model specifications. Finally, market sentiment does not influence the transmission of spread shocks, whereas, it exerts a significant effect on the spillover of price impact shocks between the ETF and its underlying portfolio (i.e., when liquidity is measured by Amihud illiquidity).

4.3. ETF arbitrage and liquidity spillover

4.3.1. Impact of arbitrage activity

ETF has a unique creation/redemption mechanism that allows ETF's Authorized Participants (APs) to arbitrage the mispricing between ETF net asset value (NAV) and its market price. Through this process, liquidity shocks from an ETF can transmit to its constituent stocks and vice versa (e.g., Ben-David, Franzoni, and Moussawi, 2018). However, we cannot measure the arbitrage activity from ETF trading data. To investigate the impact of ETF arbitrage activity on the liquidity spillover between the ETF and its underlying portfolio, we use two proxies of ETF arbitrage. Following Krause, Ehsani, and Lien (2014), we first use ETF fund flows to indicate ETF arbitrage activity. Flows into or out of ETFs are likely indicators of arbitrage activities as APs trade baskets of stocks for ETFs (and vice versa) to net their positions. Because both fund inflow and outflow might show the strength of arbitrage activity, we use absolute flow as the first proxy of ETF arbitrage activity in our paper. Consistent with Clifford, Furkerson, and Jordan (2014), and Broman and Shum (2018), we compute the daily absolute fund flows, $ABS\_FUND\_FLOW_t$, as below:

$$ABS\_FUND\_FLOW_t = |SHR_t - SHR_{t-1}| \times NAV_t / AUM_{t-1} \quad (18)$$

where SHR_t is the number of shares outstanding of ETF on day *t*; NAV_t is the net asset value per share on day *t*, AUM_{t-1} is the asset under management on day $t-1$.

Besides the above measure, we use another proxy for ETF arbitrage activity: the ETF pricing error or the absolute premium or ETF discount (PRC_ERR). ETF premium or discount is the percentage deviation of the ETF price compared to its NAV. Ben-David, Franzoni, and Moussawi (2018) use this proxy for arbitrage activity. To gauge the impact of arbitrage activity on liquidity spillover, we estimate models (13) and (14) with variables of interest being the weekly absolute fund flows ($ABS\_FUND\_FLOW_{k-1}$) and the pricing error (PRC_ERR_{k-1}) of the ETF. $ABS\_FUND\_FLOW_{k-1}$ is the average daily percentage absolute change in fund inflow or outflow of ETF in week $(k-1)$, and PRC_ERR_{k-1} is the average pricing error of ETF in week $(k-1)$. As we hypothesize that liquidity spillover increases when ETF arbitrage activity intensifies, the coefficients of $ABS\_FUND\_FLOW_{k-1}$ and PRC_ERR_{k-1} are expected to be positive and statistically significant.

The regression results of Eqs. (16) and (17) with the above variables of interest are in Table 5. We find that absolute fund flow, $ABS\_FUND\_FLOW_{k-1}$ is positively correlated with liquidity spillover between the DIAMONDS ETF and its underlying portfolio. The result suggests that arbitrage activity fuels liquidity spillover between the ETF and its underlying portfolio. This finding is robust for all model specifications when including $ABS\_FUND\_FLOW_{k-1}$. The ETF pricing error results are less impressive as PRC_ERR_{k-1} only positively relates to liquidity spillover calculated using the bid-ask spread. In addition, the regression results show asymmetrical effects of arbitrage activity on directional liquidity spillover. Specifically, we find that arbitrage activity only positively relates to the liquidity spillover from the underlying portfolio to its ETF ($WDLSI_{Underlying \to ETF}$), as shown in columns (7), (8), and (9) of Panel A and columns (7) and (9) of Panel B. On the contrary, none of the estimated parameters of $ABS\_FUND\_FLOW_{k-1}$ and PRC_ERR_{k-1} is statistically significant in model specifications (4), (5), and (6). Overall, our results in this part are consistent with Hypothesis 3 and support Ben-David, Franzoni, and Moussawi's (2018) proposition about the role of arbitrage in transmitting shocks between ETFs and underlying portfolios.

[Please insert Table 5 about here]

The results so far have shown that arbitrage activity magnifies the transmission of liquidity shocks between the ETF and its portfolio liquidity. One might be concerned about reverse causality, namely, the greater liquidity spillover expressed by either $WLSI_{k-1}$, $WDLSI_{ETF\rightarrow Underlying,k-1}$ or $WDLSI_{Underlying\rightarrow ETF,k-1}$ leads to higher arbitrage activity. To address this concern, we directly investigate the ability of liquidity spillover to predict the variation of arbitrage activity. We use the same control variables as in Eqs. (16) and (17). The results reported in Appendix A6 show that none of the liquidity spillover measures is statistically significant in forecasting arbitrage activity. This conclusion holds firmly for both proxies of arbitrage activity used and helps rule out the possibility of reverse causality. Since these results are insignificant we do not include them in the main tables to save space.

4.3.2. Impact of funding costs

Funding costs affect the liquidity spillover between the ETF and its underlying portfolio through their impact on the cost of capital available for the ETF arbitrage activity and the risk aversion of the ETF dealers. In this section, we explore the impact of several proxies.[14] For funding costs on the intensity of liquidity spillover between the DIAMONDS ETF and its underlying portfolio, these proxies are $SHORTRATE_{k-1}$ as the weekly change in the Federal Funds Rate; $TERMSPREAD_{k-1}$ as the weekly change in the difference between the yield on a

[14] These proxies are used in Huberman and Halka (2001) and Chordia, Roll, and Subrahmanyam (2002) to study the impact of funding constraints on market liquidity.

constant maturity 10-year Treasury bond and the Federal Funds Rate; $DEFAULTSPREAD_{k-1}$ as the weekly change in the difference between the yield on the Moody's Baa or better corporate bond yield index and the yield on a 10-year constant maturity Treasury bond, and YLD_STD_{k-1} as the volatility of the Treasury note measured by its weekly standard deviation.

An increase in each of the first three proxies implies higher funding costs faced by ETF arbitrageurs as they are components of funding costs. However, their effect on the ETF dealers' risk aversion may differ. The Federal Funds Rate is inversely related to the unemployment rate and directly related to several measures of expected inflation (Kesselring and Bremmer, 2011). As a result, an increase in the Federal Funds Rate might indicate lower risk aversion in the marketplace as it implies a higher employment rate and better economic activity. Similarly, an increase in $TERMSPREAD_{k-1}$ indicates that the yield curve is steepening, and the economy is expected to be stronger[15]. Consequently, an increase in $TERMSPREAD_{k-1}$ can be associated with lower risk aversion among ETF dealers. From the above discussion, we expect that the effect of $SHORTRATE_{k-1}$ and $TERMSPREAD_{k-1}$ on liquidity spillover is significantly negative.

In contrast, we expect an increase in the credit risk in the economy ($DEFAULTSPREAD_{k-1}$) implies more risk aversion in the marketplace. By intuition, default risk tends to increase during an economic slowdown or financial crisis. For instance, Hu (2020) finds that the credit default spread of US firms is highest during the peak of the Global Financial Crisis. As a result, an increase in $DEFAULTSPREAD_{k-1}$ has opposing effects on the liquidity spillover between the ETF and its underlying portfolio. A higher credit risk implies more risk

[15] https://www.stlouisfed.org/publications/regional-economist/october-1997/yielding-clues-about-recessions-the-yield-curve-as-a-forecasting-tool#:~:text=A%20steepening%20yield%20curve%E2%80%94that,term%20rates%20in%20the%20future.&text=During%20a%20recession%2C%20for%20example,the%20Fed%20eases%20monetary%20policy.

aversion, leading to higher liquidity transmission. In reverse, increasing credit risk means higher credit spread and higher funding costs, which reduce arbitrage activity and liquidity spillover. Consequently, we expect that the net effect of $DEFAULTSPREAD_{k-1}$ on liquidity spillover is uncertain.

Regarding yield volatility, Borio and McCauley (1996) find that high yield volatility is usually associated with sell-offs in bond markets. Huberman and Halka (2000) find that an increase in yield volatility reduces systematic liquidity in the stock market. Consequently, we hypothesize that an increase in YLD_STD_{k-1} will positively impact liquidity spillover as it implies more risk aversion in the marketplace.

To investigate the effect of the above funding cost proxies on liquidity spillover, we estimate Eqs. (16) and (17), with variables of interest being the set of funding cost proxies described above. Table 6 reports the regression results of Eqs. (16) and (17). We use $WLSI$, $WDLSI_{ETF\rightarrow Underlying}$, and $WDLSI_{Underlying\rightarrow ETF}$ as dependent variables in Panels A, B, and C, respectively. In Panel A, our results show a robust and significant positive correlation between default spread, $DEFAULTSPREAD_{k-1}$, with liquidity spillover. This is consistent with our expectation that the rising default spread could increase market makers' risk aversion, hence the liquidity spillover between the ETF and its underlying portfolio. A rising default spread implies an increased risk of default in the economy, affecting bondholders and stockholders. For instance, Vassalou and Xing (2004) find that default risk is a systematic risk in the stock market. Brogaard, Li, and Xia (2017) document a negative relation between default risk and stock liquidity.

In Panel A, the coefficient of yield volatility, YTD_STD_{k-1}, is also significantly positive for all model specifications. Higher yield volatility is associated with higher risk aversion among market makers. This finding is consistent with Huberman and Halka's (2004) finding that yield volatility harms market liquidity. The effect of the term spread, $TERMSPREAD_{k-1}$, is less consistent as it is positively related to liquidity spillover using the bid-ask spread as a liquidity proxy but negatively associated with liquidity spillover using the Amihud illiquidity ratio as a liquidity proxy. Finally, we find some evidence that an increase in the Fed Fund Rate, $SHORTRATE_{k-1}$ reduces liquidity spillover, according to our expectations.

In Panels B and C, we examine the effect of funding costs on the directional liquidity spillover between the ETF and its underlying portfolio. In Panel B, the variation of funding costs does not affect the liquidity spillover from the ETF to its underlying portfolio ($WDLSI_{ETF\rightarrow Underlying}$) calculated using the bid-ask spread as evidenced by the estimated parameters in column (5). However, the yield volatility (*YTD_STD*$_{k-1}$) is positively correlated with the $WDLSI_{ETF\rightarrow Underlying}$ computed using Amihud illiquidity as shown in the model specification (10). In Panel C, we find an increase in Fed Fund Rate (*SHORRATE*$_{k-1}$) reduces liquidity spillover from the ETF spread to its underlying spread as in columns (1) and (5). The effect of $TERMSPREAD_{k-1}$ is mixed, whereas $DEFAULTSPREAD_{k-1}$ only positively affects the $WDLSI_{Underlying\rightarrow ETF}$ calculated using Amihud illiquidity.

[Please insert Table 6 about here]

4.3.3. Impact of short-sale constraints on liquidity spillover

In the previous section, we find that liquidity spillover correlates with the proxy of ETF arbitrage activity. As a result, limits to arbitrage could likely reduce liquidity spillover by decreasing arbitrage activities. This part investigates if changes in the short-selling constraint of an underlying stock could affect its liquidity spillover with the ETF. This investigation is essential for two reasons. First, it is used as an indirect check for the impact of arbitrage as a channel to transmit liquidity shocks from ETF to component stocks or vice versa, documented in the last part. Second, it adds crucial empirical evidence on the effect of short-sale constraints on ETF arbitrage and the liquidity linkage between ETF and component stocks. We examine the impact of short-selling on liquidity spillover through a difference-in-difference analysis with a quasi-natural regulatory experiment on short-sale constraints. This regulatory experiment is the Regulation SHO pilot program conducted by the SEC from 2005 to 2017. The following paragraphs will describe the regulation change, design the difference-in-difference (DiD) analysis, and report the DiD results.

The SEC announced Rule 202T of Regulation SHO on July 28, 2004, to determine if a price test was necessary to further the objectives of short sale regulation and study the effect of unrestricted short selling on market volatility, price efficiency, and market liquidity. This rule contained a pilot program in which stocks in the exchanges were ranked by trading volume, and every third became a pilot stock. From May 2, 2005, to August 6, 2007, these randomly selected stocks were exempted from short-selling price tests. This regulatory change significantly reduced the short-sale constraints of pilot stocks compared to those of non-pilot stocks. This program ended on July 6, 2007, when the SEC eliminated short-selling price tests for all exchange-listed stocks. ETF arbitrage is an important channel to fuel liquidity spillover between ETF and underlying stocks. We expect the Regulation SHO pilot program to bolster pilot stocks' arbitrage activity in the ETF and increase their liquidity spillover with the ETF.

Only six stocks were among 43 constituent stocks of the DIAMONDS ETF from 2002 to 2016.[16] They were components of the ETF during the pilot program (approximately eight quarters from Q3/2005 to Q2/2007). We include a further eight quarters before the pilot program (from Q3/2003 to Q2/2005, i.e., PRE period) and eight quarters after the pilot program (from Q3/2007 to Q2/2009, i.e., $POST$ period) for the difference-in-difference analysis.

To construct the sample, we match each pilot component stock with a non-pilot component stock with the closest stock price at the end of Q2/2005. Krause, Ehsani, and Lien (2014) find that volatility spillover between an ETF and its underlying stock correlates with

[16] These tickers are DIS, HD, INTC, JNJ, KO, and WMT.

stock weights in the ETF. As DIAMONDS is a price-weighted ETF, we use the stock price as the matching criterium to reduce heterogeneity between a pilot and non-pilot stock.

For each pilot or non-pilot stock, we construct its weekly liquidity spillover index with ETF, as explained in Figure 2. For the whole period (before, during, and after the pilot program), we have 303 weekly observations of each stock's liquidity spillover index. Following Fang, Huang, and Karpoff (2016) and Kan and Gong (2018), we implement the difference-in-difference approach and estimate the following model:

$$WLSI_{i,k} = \alpha + \beta_1 PILOT_{i,k} \times DURING_{i,k} + \beta_2 PILOT_{i,k} \times POST_{i,k} + \beta_3 PILOT_{i,k} + \beta_4 DURING_{i,k} + \beta_5 POST_{i,k} + Controls_{i,k} + \varepsilon_k \qquad (19)$$

where $WLSI_{i,k}$ is the *Weekly Liquidity Spillover Index* between component stock i with the DIAMONDS ETF using the bid-ask spread or Amihud illiquidity ratio as a liquidity measure. $PILOT_{i,k}$ equals one if stock i is in the pilot group and zero otherwise. $DURING_{i,k}$ equals one if the weekly liquidity spillover index's end date is between Q3/2005 to Q2/2007 and zero otherwise. $POST_{i,k}$ equals one if the weekly liquidity spillover index's end date is between Q3/2007 to Q2/2009 and zero otherwise. $Controls_{i,k}$ is a set of control variables to consider the pilot and non-pilot stocks' trading characteristics. These trading characteristics are stock market capitalization, stock return volatility, stock turnover, and stock weight in the ETF portfolio.[17] We expect the coefficient β_1 to be significantly positive, which implies that relaxing the short-sale constraints positively impacts the liquidity spillover of pilot component stocks with ETF.

Table 7 presents the regression results of Eq. (19). The sign of the interaction between $PILOT$ and $DURING$ is significantly positive for all model specifications suggesting the ETF

[17] The effect of these control variables on liquidity spillover between individual stocks and the ETF is shown in Appendix A7.

arbitrage activity increases for pilot component stocks and positively affects the liquidity spillover between the ETF and its pilot component stocks. Overall, the results of the difference-in-difference analysis suggest that by involving ETF arbitrage, short-sale constraints inversely correlate with liquidity linkage between an ETF and its component stocks.

[Please insert Table 7 about here]

5. Conclusion

Market liquidity has a crucial role in maintaining a well-functioning capital market. As a result, market liquidity dry-ups have drawn significant interest from investors, researchers, and market regulators. While market illiquidity can be due to liquidity spillover between assets and their liquidity commonality, empirical studies on liquidity spillover are limited. This paper fills this literature gap by presenting novel evidence about liquidity spillover between the DIAMONDS ETF and its component stocks. It also investigates the empirical relevance of the theoretical literature's transmission channels to explain liquidity spillover.

Our empirical findings indicate that liquidity spillover between the ETF and its underlying portfolio is significant. Furthermore, it intensifies during an economic slowdown and positively relates to market volatility and funding constraints. Finally, liquidity spillover varies proportionally with ETF arbitrage activity and tends to be lower when short sales constraints exist.

The results of our paper have two important policy implications given the fast-growing ETF market. First, the significant liquidity spillover between an ETF and its underlying portfolio, especially during a market crisis or economic downturn, suggests that the risk of liquidity contagion between these two markets is high and should be monitored closely. Second, short-sale constraints can reduce the magnitude of liquidity spillover, and this measure can be used during a market crisis to lessen market liquidity's dry-ups.

There are several interesting future studies one might take when examining the liquidity spillover between ETF and underlying portfolio. First, in this paper, we assume the magnitude of the liquidity spillover depends on macroeconomic conditions, fund flows, pricing errors, funding constraints, and short-sale constraints. However, this list of explanatory variables is not exhaustive. For instance, Piccotti (2018) and Bae and Kim (2020) suggest that ETF tracking errors are significantly related to ETF liquidity. As such, future research may explore the impact of ETF tracking errors as a possible driver of the interconnectedness between ETF and underlying liquidity. Second, as our study examines the liquidity spillover of only one ETF (e.g., DIAMONDS ETF), our cross-sectional analysis is limited. As a result, exploring the liquidity connectedness using a large sample of ETFs might represent a possible venue for further research. Finally, it would be interesting to examine the evolvement of the liquidity spillover in the ETF market during recent global events such as the US-China trade war, the COVID-19 pandemic, and the Russia-Ukraine war.

References

Alexander, C., & Barbosa, A. (2008). Hedging index exchange traded funds. *Journal of Banking & Finance*, *32* (2), 326-337.

Alizadeh, S., Brandt, M. W., & Diebold, F. X. (2002). Range-based estimation of stochastic volatility models. *Journal of Finance, 57*, 1047–91.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets, 5* (1), 31–56.

Amihud, Y., & Mendelson, H. (1986). Liquidity and stock returns. *Financial Analysts Journal*, *42* (3), 43-48.

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid ask spread. *Journal of Financial Economics, 17* (2), 223-249.

Antonakakis, N., & Vergos, K. (2013). Sovereign bond yield spillovers in the Euro zone during the financial and debt crisis. *Journal of International Financial Markets, Institutions and Money, 26*, 258–272.

Bae, K., & Kim, D. (2020). Liquidity risk and exchange-traded fund returns, variances, and tracking errors. *Journal of Financial Economics*, *138*(1), 222-253.

Bandopadhyaya, A., & Jones, A. L. (2008). Measures of investor sentiment: A comparative analysis of put-call ratio vs. volatility index. *Journal of Business and Economics Research, 6* (8), 27–34.

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do ETFs increase volatility? *Journal of Finance, 73* (6), 2471–2534.

Bhattacharya, A., & O'Hara, M. (2016). Can ETFs increase market fragility? Effect of information linkages in ETF markets? *Available at SSRN:* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2740699.

Bhattacharya, A., & O'Hara, M. (2020). ETFs and systematic risks? *CFA Institute Research Foundation*.

Borio, C., & McCauley, R. N. (1996). The economics of recent bond yield volatility. *BIS Economic Papers.*

Bradrania, M. R., Peat, M., & Satchell, S. (2015). Liquidity costs, idiosyncratic volatility and expected stock returns. *International Review of Financial Analysis, 42*, 394-406.

Brogaard, J., Li, D., & Xia, Y. (2017). Stock liquidity and default risk. *Journal of Financial Economics, 124* (3), 486–502.

Broman, M. S., & Shum, P. (2018). Relative liquidity, fund flows and short-term demand: Evidence from Exchange-Traded Funds. *Financial Review, 53*, 87–115.

Brumnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial studies, 22* (6), 2201–2238.

Cespa, G., & Foucault, T. (2014). Illiquidity contagion and liquidity crashes. *Review of Financial Studies*, *27* (6), 1615–1660.

Chan, L., & Lien, D. (2003). Using high, low, open, and closing prices to estimate the effects of cash settlement on future prices. *International Review of Financial Analysis, 12*, 35–47.

Chordia, T., Roll, R., & Subrahmanyam, A. (2002). Market liquidity and trading activity. *The Journal of Finance, 56*, 501–530.

Chordia, T., Sarkar, A., & Subrahmanyam, A. (2005). An empirical analysis of stock and bond market liquidity. *Review of Financial Studies*, *18* (1), 85–129.

Chung, K. H., & Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets*, *17*, 94-120.

Clements, R. (2018). Safe until they aren't? Investigating liquidity illusion in exchange traded fund market. *Retrieved from:* https://sites.law.duke.edu/thefinregblog/2018/12/06/safe-until-they-arent-investigating-liquidity-illusions-in-the-exchange-traded-fund-market/

Clements, R. (2020). New funds, familiar fears: Do exchange-traded funds make markets less stable? Part I, liquidity illusions. *Available at SSRN*: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3343976.

Clifford, C. P., Fulkerson, J. A., & Jordan, B. (2014). What drives ETF flows? *Financial Review, 49*, 619–642.

Copeland, T. E., & Galai, D. (1983). Information effects on the bid-ask spread. *Journal of Finance, 38* (5), 1457–1469.

Datar, V. T., Naik, N. Y., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of financial markets*, *1*(2), 203-219.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldman, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy, 98* (4), 703–738.

Dennis, P., & Mayhew, S. (2002). Risk-neutral skewness: Evidence from stock options. *Journal of Financial and Quantitative Analysis, 37* (3), 471–493.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillover. *International Journal of Forecasting, 28* (1), 57–66.

Diebold, F. X., & Yilmaz. K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal., 119* (534), 158–171.

Engelberg, J. E., Reed, A. V., & Ringgenberg, M. C. (2012). How are shorts informed? Short sellers, news, and information processing. *Journal of Financial Economics, 105* (2), 260–278.

Fang, V. W., Huang A. H., & Karpoff, J. M. (2016). Short selling and earning management: A controlled experiment. *Journal of Finance, 71*, 1251–1294.

Florackis, C., Gregoriou, A., & Kostakis, A. (2011). Trading frequency and asset pricing on the London Stock Exchange: Evidence from a new price impact ratio. *Journal of Banking & Finance, 35* (12), 3335-3350.

Fung, J. K. W., & Draper, P. (1999). Mispricing of index futures contracts and short sales constraints. *Journal of Future Markets, 19* (6), 695–715.

Gallan, A. R., Rossi, P. E., & Tauchen, G. (1992). Stock prices and volume. *Review of Financial Studies, 5* (2), 199–242.

Gay, G. D., & Jung, D. Y. (1999). A further look at transaction costs, short sale restrictions, and futures market efficiency: The case of Korean stock index futures. *Journal of Future Markets, 19*, 153–174.

Glosten, L. R., & Harris, L. E. (1988). Estimating the components of the bid/ask spread. *Journal of Financial Economics, 21* (1), 123–142.

Goyenko, R. Y., & Ukhov, A. D. (2009). Stock and bond market liquidity: A long-run empirical analysis. *Journal of Financial and Quantitative Analysis*, *44* (1), 189–212.

Guo, W. (2004). Some evidence in the trading and pricing of equity LEAPS. *International Review of Economics and Finance, 13* (4), 407–426.

Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity. *The Journal of finance*, *65*(1), 257-293.

Hasbrouck, J., & Seppi, D. J. (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics, 59* (3), 383–411.

Hegde, S. P., & McDermott, J. B. (2004). The market liquidity of DIAMONDS, Q's, and their underlying stocks. *Journal of Banking & Finance*, *28*(5), 1043-1067.

Hill, J., Nadig, D., Hougan, M., & Fuhr, D. (2015). *A comprehensive guide to exchange-traded funds*. CFA Institute Research Foundation.

Hong, Y., Lin, H., & Wu, C. (2012). Are corporate bond market returns predictable? *Journal of Banking and Finance*, *36*, 2216–2232.

Hu, G. X. (2020). Rollover risk and credit spread in the financial crisis of 2008. *Journal of Finance and Data Science, 6*, 1-15.

Huberman, G., & Halka, D. (2001). Systematic liquidity. *Journal of Financial Research, 24*, 161–178.

Ivanov, S. I. (2013). High-frequency analysis of exchange traded funds' pricing deviation. *Managerial Finance*, *39*(5), 509-524.

Jun, S. G., Marathe, A., & Shawky, H. A. (2003). Liquidity and stock returns in emerging equity markets. *Emerging Markets Review*, *4*(1), 1-24.

Kan, S., & Gong, S. (2018). Does high stock return synchronicity indicate high or low price informativeness? Evidence from a regulatory experiment. *International Review of Finance, 18,* 523–546.

Karolyi, G. A., Lee, K. H., & van Dijk, M.A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics, 105* (1), 82–112.

Kesselring, R., & Bremmer, D. S. (2011). Setting the target for the federal funds rate: the determinants of Fed behaviour. *Applied Economics, 43* (11), 1341-1349.

Kodres, L. E., & Pritsker, M. (2002). A rational expectations model of financial contagion. *Journal of Finance, 57* (2), 769–799.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics, 74* (1), 119–147.

Krause, T., Ehsani, S., & Lien, D. (2014) Exchange-traded funds, liquidity and volatility. *Applied Financial Economics*, *24*, 1617–1630.

Kumar, S., & Prasanna, K. (2018). Liquidity in Asian markets: Intensity of regional and global linkages. *Applied Economics*, *50* (55), 6010–6023.

Kyle, A. S., & Xiong, W. (2001). Contagion as a wealth effect. *Journal of Finance, 56* (4), 1401–1440.

Lam, K. S. D., & Tam, L. H. K. (2011). Liquidity and asset pricing: Evidence from the Hong Kong stock market. *Journal of Banking & Finance, 35* (9), 2217-2230.

Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking and Finance, 26* (12), 2277–2299.

Lin, W. L., Engle, R., & Ito, T. (1994). Do bulls and bears move across borders? International transmission of stock returns and volatility. *Review of Financial Studies, 7* (3), 507–538.

Mancini-Griffoli, T., & Ranaldo, A. (2010). Limits to arbitrage during the crisis: Funding liquidity constraints and covered interest parity. *Available at SSRN:* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1569504.

Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2018). Do liquidity proxies measure liquidity accurately in ETFs? *Journal of International Financial Markets, Institutions and Money, 55*, 94–111.

Neal, R. (1996). Direct tests of index arbitrage models. *Journal of Financial and Quantitative Analysis, 31* (4), 541–562.

O'Hara, M., & Oldfield, G. S. (1986). The microeconomics of market making. *Journal of Financial and Quantitative Analysis, 21* (4), 361-376.

Ofek, E., Richardson, M., & Whitelaw, R. F. (2004). Limited arbitrage and short sales restrictions: evidence from the options markets. *Journal of Financial Economics, 74* (2), 305–342.

Pagano, M., Serrano, A. S., & Zechner, J. (2019). Can ETFs contribute to systematic risk? *Reports of the Advisory Scientific Committee, European Systematic Risk Board*. No 9.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business, 53*, 61–65.

Pasquariello, P. (2007). Imperfect competition, information heterogeneity, and financial contagion. *Review of Financial Studies, 20* (2), 391–426.

Pástor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111* (3), 642–685.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economic Letters, 58* (1), 17–29.

Piccotti, L. R. (2018). ETF premiums and liquidity segmentation. *Financial Review*, *53*(1), 117-152.

Reyes, M. G. (2001). Asymmetry volatility spillover in the Tokyo Stock Exchange. *Journal of Economics and Finance, 25*, 206–213.

Rösch, C. G., & Kaserer, C. (2014). Reprint of: Market liquidity in the financial crisis: The role of liquidity commonality and flight-to-quality. *Journal of Banking and Finance, 45*, 152–170.

Shen, P., & Starr, R. M. (2002). Market-makers' supply and pricing of financial market liquidity. *Economics Letters, 76* (1), 53–58.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance, 52*, 35–55.

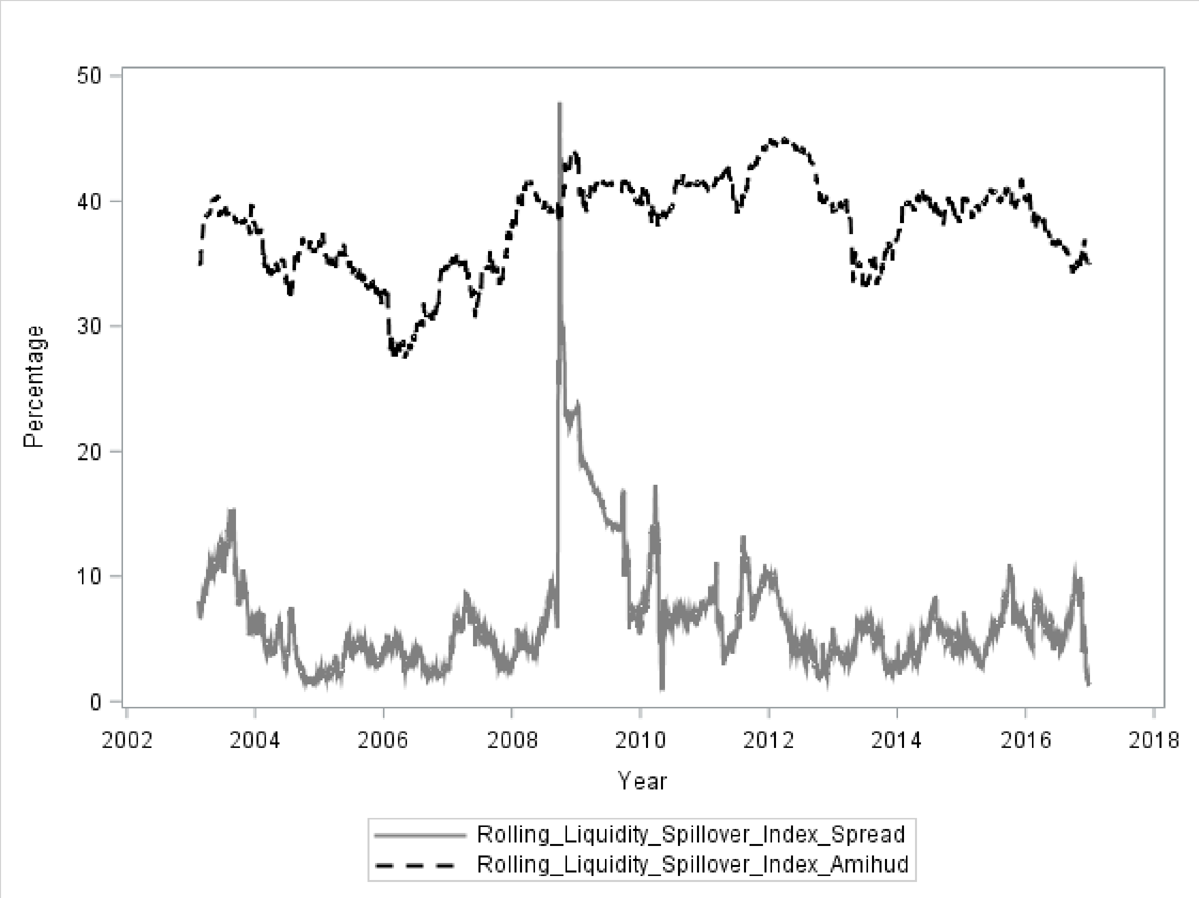
Stoll, H. R. (2000). Presidential address: Friction. *Journal of Finance, 55,* 1479-1514.

Su, E., (2018). Exchange-Traded Funds (ETFs): issues for Congress. *Congressional Research Service Report*, No R45318.

Vassalou, M., & Xing, Y. (2004). Default risk in equity returns. *Journal of Finance, 59* (2), 831–868.

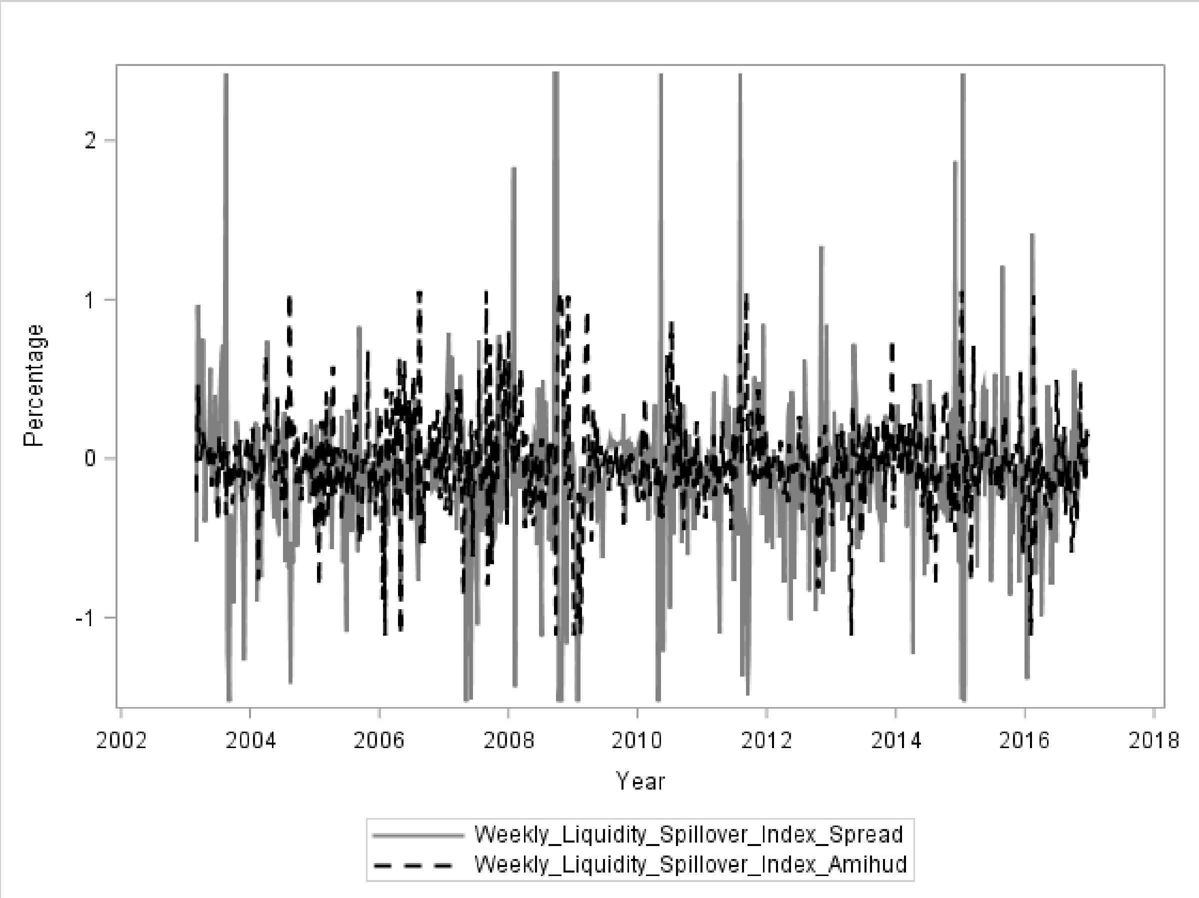
Wei, J. K. C, Liu, Y., Yang, C., & Chaung, G. (1995). Volatility and price change spillover effects across the developed and emerging markets. *Pacific-Basin Finance Journal, 3* (1), 113–136.

Figure 1. Rolling Liquidity Spillover Index 2002-2016



This figure plots the rolling *Liquidity Spillover Index* (as defined in Eq. (15)) using 200-day moving window between 2002 and 2016 for the DIAMONDS ETF. The solid line is the rolling liquidity spillover index using the quoted bid-ask spread as a liquidity proxy and the broken line is the rolling liquidity spillover index using the Amihud illiquidity ratio as a liquidity proxy.

Figure 2. Weekly Liquidity Spillover Index 2002-2016



This figure plots the *Weekly Liquidity Spillover Index* (*WLSI*) over the research period. The solid line is the *WLSI* using the quoted bid-ask spread as a liquidity proxy and the broken line is the *WLSI* using the Amihud illiquidity ratio as a liquidity proxy. *WLSI* is calculated as the difference between the rolling *LSI* using the 205-day window and 5-day lagged value of the rolling *LSI* using the 200-day window.

Table 1. Descriptive Statistics, Diagnostic Tests, and Correlation Matrix of Variables in VAR Model

Panel A. Descriptive statistics

Variable	Mean	Median	Standard Deviation	Min	Max	Kurtosis	Skewness	Q(1)	Q(5)	Q(20)
$QSPR_E$	0.0130	0.0100	0.0140	0.0050	0.3030	189.6800	8.1600	418***	2073***	6978***
$Amihud_E$	0.0007	0.0006	0.0008	0.0000	0.0130	3.9100	1.5600	51***	458***	1663***
VOL_E	0.0620	0.0580	0.0210	0.0250	0.2090	5.5900	1.9900	250***	874***	1949***
RET_E	0.0360	0.0740	1.1260	7.5200	13.5600	6.1200	0.0800	18***	37***	59.05***
$QSPR_U$	0.0540	0.0300	0.0710	0.0100	0.6420	12.4700	1.8800	215***	1003***	3702***
$Amihud_U$	0.0024	0.0018	0.0017	0.0004	0.0250	5.6500	1.9000	351***	1761***	7893***
VOL_U	0.0110	0.0094	0.0060	0.0040	0.0870	7.1200	2.2900	250***	789***	2169***
RET_U	0.0440	0.0610	1.1000	-7.4950	10.510	5.3400	0.0600	23***	43***	62.90***

Panel B. Results of stationarity tests

	$QSPR_E$	$Amihud_E$	VOL_E	RET_E	$QSPR_U$	$Amihud_U$	VOL_U	RET_U
ADF Test	-14.82***	-16.88***	-7.07***	-40.22***	-9.09***	-11.73***	-5.16***	-40.42***
PP Test	-31.36***	-38.02***	-6.23***	-60.40***	-11.49***	-25.07***	-4.51***	-61.09***

Panel C. Correlation matrix

	$QSPR_E$	$Amihud_E$	VOL_E	RET_E	$QSPR_U$	$Amihud_U$	VOL_U	RET_U
$QSPR_E$	1							
$Amihud_E$	0.286	1						
VOL_E	0.319	0.297	1					
RET_E	0.056	0.079	0.043	1				
$QSPR_U$	0.680	0.363	0.417	-0.062	1			
$Amihud_U$	0.505	0.742	0.418	0.023	0.674	1		
VOL_U	0.383	0.272	0.913	0.046	0.489	0.449	1	
RET_U	-0.065	0.083	0.046	0.986	-0.049	0.031	0.055	1

This table reports the descriptive statistics, the results of unit root tests, and the correlation matrix of variables in the following VAR model:

$$X_t = \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + \varepsilon_t \quad (12)$$
$$Y_t = \sum_{j=1}^{k} \mu_j Y_{t-j} + \sum_{j=1}^{k} \lambda_j X_{t-j} + \phi_t \quad (13)$$

where X and Y are vectors representing daily values liquidity, return, and volatility of the DIAMONDS ETF and those of the underlying portfolio, respectively. The above VAR system includes a 6-equation vector autoregression specification that incorporates six variables: three for the ETF (liquidity: $LIQ_{E,t}$, return: $RET_{E,t}$, and volatility: $VOL_{E,t}$) and three for the underlying portfolio (liquidity: $LIQ_{U,t}$, return: $RET_{U,t}$, and volatility: $VOL_{U,t}$). Liquidity can be proxied by either the quoted bid-ask spread ($QSPR_{E,t}$ and $QSPR_{U,t}$) or Amihud illiquidity ratio ($Amihud_{E,t}$ and $Amihud_{U,t}$). Our research period ranges from 1st April 2012 to 31st December 2016, encompassing 3689 daily observations. In Panel A, Q(1), Q(5), and Q(20) denote the Ljung-Box statistics for 1, 5, and 20 lags. In Panel B, ADF Test refers to the Augmented Dickey Fuller (ADF) test, and PP test refers to Phillips-Perron test. The test regressions do not include individual intercept and time trend. Lag lengths are selected based on the AIC. The null hypothesis for both tests is there is a unit root in the time series. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2. Granger Causality Tests

Panel A. Using quoted bid-ask spread as liquidity measure

	$QSPR_E$	VOL_E	RET_E	$QSPR_U$	VOL_U	RET_U
$QSPR_E$		18.8	22.9	55.6	9.8	27.4
		(0.0046)	(0.0008)	(0.0001)	(0.1340)	(0.0001)
VOL_E	90.3		6.7	31.0	25.5	7.0
	(0.0001)		(0.3460)	(0.0001)	(0.0003)	(0.3170)
RET_E	30.9	343.7		34.9	289.5	2.1
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.9130)
$QSPR_U$	254.3	38.4	16.1		50.9	19.3
	(0.0001)	(0.0001)	(0.0133)		(0.0001)	(0.0037)
VOL_U	88.1	48.7	17.3	22.5		15.7
	(0.0001)	(0.0001)	(0.0080)	(0.0010)		(0.0150)
RET_U	29.3	345.4	5.7	36.1	282.1	
	(0.0001)	(0.0001)	(0.4530)	(0.0001)	(0.0001)	

Panel B. Using Amihud illiquidity as liquidity measure

	$Amihud_E$	VOL_E	RET_E	$Amihud_U$	VOL_U	RET_U
$Amihud_E$		49.2	8.4	48.4	37.5	7.3
		(0.0001)	(0.2110)	(0.0010)	(0.0001)	(0.2900)
VOL_E	101.1		6.7	103.1	25.5	7.0
	(0.0001)		(0.3460)	(0.0001)	(0.0003)	(0.3170)
RET_E	79.8	343.7		160	289.5	2.1
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.9130)
$Amihud_U$	45.6	38.3	14.1		36.1	12.9
	(0.0001)	(0.0001)	(0.0290)		(0.0001)	(0.0450)
VOL_U	88.9	48.7	17.3	81.0		15.7
	(0.0001)	(0.0001)	(0.0080)	(0.0001)		(0.0150)
RET_U	76.0	345.4	5.7	153.2	282.1	
	(0.0010)	(0.0001)	(0.4530)	(0.0001)	(0.0001)	

This table reports the Chi-square statistics and p-values (in parenthesis) of pairwise Granger causality tests between the endogenous variables in the VAR model:

$$X_t = \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + \varepsilon_t \quad (12)$$

$$Y_t = \sum_{j=1}^{k} \mu_j Y_{t-j} + \sum_{j=1}^{k} \lambda_j X_{t-j} + \phi_t \quad (13)$$

where *X* and *Y* are vectors representing daily values liquidity, return, and volatility of the DIAMONDS ETF and those of the underlying portfolio, respectively. The above VAR system includes a 6-equation vector autoregression specification that incorporates six variables: three for the ETF (liquidity: $LIQ_{E,t}$, return: $RET_{E,t}$, and volatility: $VOL_{E,t}$) and three for the underlying portfolio (liquidity: $LIQ_{U,t}$, return: $RET_{U,t}$, and volatility: $VOL_{U,t}$). Liquidity can be proxied by either the quoted bid-ask spread ($QSPR_{E,t}$ and $QSPR_{U,t}$) or Amihud illiquidity ratio ($Amihud_{E,t}$ and $Amihud_{U,t}$). Lag lengths are selected based on the AIC. The null hypothesis is that a row variable does not Granger-cause a column variable.

Table 3. Direction and Magnitude of Spillover

Panel A. Using quoted bid-ask spread as liquidity measure

	$QSPR_E$	VOL_E	RET_E	$QSPR_U$	VOL_U	RET_U	From others
$QSPR_E$	78.76	2.64	2.36	10.87	3.05	2.32	21.24
VOL_E	0.38	44.62	11.49	1.12	31.08	11.32	55.38
RET_E	0.65	1.81	48.12	0.55	1.71	47.16	51.88
$QSPR_U$	4.90	2.69	1.69	84.62	4.33	1.76	15.38
VOL_U	0.46	30.19	11.12	2.51	45.06	10.66	54.94
RET_U	0.71	1.72	47.13	0.63	1.69	48.11	51.89
To others	7.11	39.05	73.79	15.67	41.86	73.23	
Including own	85.87	83.67	121.91	100.29	86.92	121.34	
Net spillover	-14.13	-16.33	21.91	0.29	-13.08	21.34	
Total Spillover Index: 41.78%							
Liquidity Spillover Index 7.89%							

Panel B. Using Amihud Illiquidity as liquidity measure

	$Amihud_E$	VOL_E	RET_E	$Amihud_U$	VOL_U	RET_U	From others
$Amihud_E$	54.35	4.41	2.63	33.75	2.24	2.62	45.65
VOL_E	2.60	40.98	11.57	4.86	28.59	11.40	59.02
RET_E	0.98	1.90	48.07	0.28	1.65	47.12	51.93
$Amihud_U$	28.49	7.54	4.25	48.86	6.75	4.11	51.14
VOL_U	1.35	28.88	11.45	4.71	42.62	10.99	57.38
RET_U	0.99	1.82	47.16	0.26	1.63	48.14	51.86
To others	34.41	44.56	77.06	43.86	40.86	76.24	
Including own	88.76	85.53	125.13	92.73	83.48	124.38	
Net spillover	-11.24	-14.47	25.13	-7.27	-16.52	24.38	
Total Spillover Index: 52.83%							
Liquidity Spillover Index 31.12%							

This table reports the direction and the magnitude of spillover between stock and ETF market liquidity and trading variables. The Total Spillover Index and the Liquidity Spillover Index are computed following Eqs. (8) and (15), respectively.

Table 4. Liquidity Spillover and Market Conditions

Panel A. Using quoted bid-ask spread as liquidity measure

	$WLSI$			$WDLSI_{ETF\rightarrow Underlying}$			$WDLSI_{Underlying\rightarrow ETF}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF_CAP	0.18	0.17	0.18	0.21	0.23	0.21	0.01	-0.01	0.02
	(1.47)	(1.42)	(1.49)	(1.31)	(1.45)	(1.29)	(0.05)	(-0.09)	(0.11)
ETF_VOLUME	-0.05	-0.05	-0.05	0.002	0.002	0.002	-0.08	-0.09	-0.09
	(-0.73)	(-0.79)	(-0.71)	(0.02)	(0.22)	(0.02)	(-1.03)	(-1.16)	(-0.98)
PMI_D	-0.12**	-0.13**	-0.12**	-0.08	-0.06	-0.08	-0.06	-0.08	-0.06
	(-2.01)	(-2.17)	(-2.02)	(-0.97)	(-0.76)	(-0.96)	(-0.89)	(-1.23)	(-0.93)
MKT_RET	-0.56	-0.32	-0.55	1.54	0.93	1.54	-0.77	0.04	-0.75
	(-0.59)	(-0.36)	(-0.57)	(1.02)	(0.65)	(1.01)	(-0.58)	(0.03)	(-0.55)
MKT_STD	11.28***	10.67**	11.30***	-6.59	-4.78	-6.60	11.21**	9.45**	11.27**
	(2.87)	(2.64)	(2.88)	(-1.24)	(-0.88)	(-1.25)	(2.36)	(1.98)	(2.39)
PCR	-0.14		-0.20	0.49		0.53	-0.53		-0.73
	(-0.49)		(-0.64)	(1.06)		(1.08)	(-1.48)		(-1.59)
HLR		-0.003	-0.006		-0.003	0.003		-0.002	-0.002
		(-0.55)	(-0.74)		(-0.25)	(0.29)		(-0.79)	(-1.51)
Intercept	-2.31	-2.25	-2.33	-4.98	-5.24	-4.95	1.45	1.78	1.38
	(-0.85)	(-0.81)	(-0.87)	(-1.32)	(-1.41)	(-1.32)	(0.48)	(0.61)	(0.44)
Number of observations	666	666	666	666	666	666	666	666	666
R-squared	0.023	0.023	0.024	0.014	0.012	0.014	0.012	0.008	0.015

Panel B. Using Amihud illiquidity as liquidity measure

	$WLSI$			$WDLSI_{ETF\rightarrow Underlying}$			$WDLSI_{Underlying\rightarrow ETF}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF_CAP	-0.12	-0.09	-0.11	-0.13	-0.11	-0.11	-0.10	-0.08	-0.09
	(-1.45)	(-1.19)	(-1.34)	(-1.37)	(-1.23)	(-1.31)	(-1.34)	(-1.19)	(-1.25)
ETF_VOLUME	-0.08*	-0.07*	-0.08*	-0.11**	-0.11**	-0.11**	-0.04	-0.03	-0.04

	(-1.89)	(-1.71)	(-1.85)	(-2.41)	(-2.24)	(-2.39)	(-1.03)	(-0.78)	(-1.01)
PMI_D	-0.15***	-0.15***	-0.15***	-0.13***	-0.13***	-0.14***	-0.16***	-0.15***	-0.16***
	(-3.92)	(-3.84)	(-3.98)	(-3.18)	(-3.17)	(-3.23)	(-3.76)	(-3.63)	(-3.83)
MKT_RET	0.56	0.44	0.57	0.41	0.32	0.43	0.53	0.28	0.54
	(0.78)	(0.59)	(0.79)	(0.64)	(0.46)	(0.67)	(0.67)	(0.39)	(0.71)
MKT_STD	12.34***	13.41***	12.37***	15.02***	15.57***	15.07***	8.56***	9.54***	8.67***
	(4.11)	(4.48)	(4.15)	(5.38)	(5.76)	(5.40)	(2.95)	(3.31)	(2.99)
PCR	0.47**		0.39*	0.43*		0.24	0.46**		0.32
	(2.21)		(1.69)	(1.74)		(1.32)	(2.24)		(1.46)
HLR		-0.002***	-0.002**		-0.002**	-0.002**		-0.002***	-0.002***
		(-3.12)	(-2.51)		(-2.52)	(-2.01)		(-3.34)	(-2.79)
Intercept	3.01*	2.78	2.95*	3.74*	3.57*	3.63*	2.17	1.86	2.11
	(1.77)	(1.62)	(1.66)	(1.92)	(1.86)	(1.88)	(1.16)	(1.01)	(1.09)
Number of observations	666	666	666	666	666	666	666	666	666
R-squared	0.062	0.067	0.071	0.055	0.058	0.060	0.051	0.053	0.055

This table reports the regression results of the following regression models:

$$WLSI_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \quad (16)$$

$$WDLSI_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \quad (17)$$

where $WLSI_k$ and $WDLSI_k$ are the *Weekly Liquidity Spillover Index* and *Weekly Directional Liquidity Spillover Index* between the DIAMONDS ETF and its underlying portfolio using either the bid-ask spread or Amihud illiquidity ratio in week k, respectively. ETF_CAP_{k-1} and ETF_VOLUME_{k-1} are control variables in week $(k-1)$ ($Controls_{k-1}$). ETF_CAP_{k-1} is the logarithm of weekly average market capitalization of the ETF measured in million dollars. ETF_VOLUME_{k-1} is the logarithm of weekly average trading volume of the ETF measured in thousands of shares. PMI_D_{k-1}, MKT_RET_{k-1}, MKT_STD_{k-1}, PCR_{k-1}, and HLR_{k-1} are variables of interest in week $(k-1)$ ($Interest_{k-1}$). PMI_D_{k-1} is a dummy variable for economic expansion, which equals 1 if the PMI is higher than 50 and zero otherwise. MKT_RET_{k-1} is the weekly market return measured as the weekly return of the S&P500 index. MKT_STD_{k-1} is the weekly market volatility measured as the standard deviation of market return for one week. PCR_{k-1} is the weekly average of the daily put-call ratio of stocks on New York Stock Exchange. HLR_{k-1} is the weekly average of the high-low index of stocks in S&P 500 index. The number in the parenthesis is the *t*-statistics of the parameter estimate. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5. Liquidity Spillover and Creation/Redemption Activity

Panel A. Using quoted bid-ask spread as liquidity measure

	$WLSI$			$WDLSI_{ETF \to Underlying}$			$WDLSI_{Underlying \to ETF}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF_CAP	0.19*	0.31***	0.30***	0.18	0.17	0.17	-0.0003	0.06	0.06
	(1.74)	(3.11)	(3.08)	(1.23)	(1.14)	(1.11)	(-0.04)	(0.76)	(0.76)
ETF_VOLUME	0.02	-0.07	-0.09	-0.11	-0.09	-0.11	-0.05	-0.06	-0.06
	(0.67)	(-1.43)	(-1.61)	(-1.59)	(-1.25)	(-1.52)	(-0.92)	(-1.02)	(-1.11)
ABS_FUND_FLOW	2.89**		2.43**	1.67		1.71	2.46*		2.34*
	(2.46)		(2.14)	(1.09)		(1.14)	(1.84)		(1.75)
PRC_ERR		2.47***	2.36***		-0.08	-0.15		1.31*	0.12
		(4.83)	(4.64)		(-0.14)	(-0.31)		(1.68)	(1.03)
Intercept	-2.82	-4.62*	-4.31*	-1.38	-1.59	-1.29	0.25	-0.36	-0.09
	(-1.16)	(-1.81)	(-1.67)	(-0.36)	(-0.41)	(-0.32)	(0.08)	(-0.13)	(-0.03)
Number of observations	666	666	666	666	666	666	666	666	666
R-squared	0.015	0.031	0.039	0.009	0.009	0.011	0.008	0.004	0.009

Panel B. Using Amihud illiquidity as liquidity measure

	$WLSI$			$WDLSI_{ETF \to Underlying}$			$WDLSI_{Underlying \to ETF}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF_CAP	-0.07	-0.07	-0.08	-0.06	-0.05	-0.06	-0.07	-0.08	-0.09
	(-1.12)	(-1.04)	(-1.16)	(-1.02)	(-0.76)	(-0.84)	(-0.72)	(-0.92)	(-1.02)
ETF_VOLUME	0.02	0.03	0.02	0.05	0.04	0.04	-0.01	0.05	0.02
	(0.32)	(1.02)	(0.40)	(1.51)	(1.33)	(1.15)	(-0.15)	(1.53)	(0.70)
ABS_FUND_FLOW	2.14***		2.17***	1.01		0.52	2.91***		2.99***
	(2.89)		(2.92)	(1.35)		(1.25)	(3.65)		(3.58)
PRC_ERR		0.002	-0.11		0.35	0.31		-0.36	-0.45
		(0.01)	(-0.32)		(0.98)	(0.88)		(-0.95)	(-1.28)
Intercept	1.01	0.76	1.10	0.59	0.31	0.37	0.98	0.88	1.29

	(0.65)	(0.48)	(0.62)	(0.36)	(0.19)	(0.23)	(0.58)	(0.51)	(0.72)
Number of observations	666	666	666	666	666	666	666	666	666
R-squared	0.018	0.006	0.018	0.008	0.008	0.009	0.024	0.005	0.025

This table reports the regression results of the following regression models:

$$WLSI_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \quad (16)$$

$$WDLSI_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \quad (17)$$

where $WLSI_k$ and $WDLSI_k$ are the *Weekly Liquidity Spillover Index* and *Weekly Directional Liquidity Spillover Index* between the DIAMONDS ETF and its underlying portfolio using either the bid-ask spread or Amihud illiquidity ratio in week k, respectively. ETF_CAP_{k-1} and ETF_VOLUME_{k-1} are control variables in week $(k-1)$ ($Controls_{k-1}$). ETF_CAP_{k-1} is the logarithm of weekly average market capitalization of the ETF measured in million dollars. ETF_VOLUME_{k-1} is the logarithm of weekly average trading volume of the ETF measured in thousands of shares. $ABS\_FUND\_FLOW_{k-1}$ and PRC_ERR_{k-1} are variables of interest in week $(k-1)$ ($Interest_{k-1}$). $ABS\_FUND\_FLOW_{k-1}$ is the average of the daily percentage absolute change in fund inflow or outflow of the ETF in one week. PRC_ERR_{k-1} is the average pricing error of the ETF for one week. Daily pricing error is measured as the absolute value of ETF premium or discount. The number in the parenthesis is the *t*-statistics of the parameter estimate. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6. Liquidity Spillover and Funding Costs

Panel A. Using WLSI

	Bid-ask spread					Amihud				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF_CAP	0.15	0.18*	0.15	0.23**	0.18*	-0.09	-0.08	-0.09	-0.06	-0.07
	(1.55)	(1.86)	(1.21)	(2.48)	(1.71)	(-1.37)	(-1.29)	(-1.59)	(-0.71)	(-1.36)
ETF_VOLUME	0.02	0.05	0.05	-0.03	-0.06	0.03	0.03	0.002	-0.003	-0.03
	(0.51)	(1.18)	(0.21)	(-0.76)	(-1.41)	(0.09)	(0.91)	(0.11)	(-0.17)	(-0.92)
$SHORTRATE$	-0.06***				-0.27	0.001				-0.19
	(-2.87)				(-1.08)	(0.01)				(-1.02)
$TERMSPREAD$		0.31**			0.29		-0.25**			-0.29**
		(2.55)			(1.61)		(-2.56)			(-2.19)
$DEFAULTSPREAD$			0.91***		0.95***			0.65***		0.38*
			(3.42)		(3.11)			(3.25)		(1.87)
YLD_STD				2.75***	1.97***				1.11**	1.01**
				(3.15)	(2.60)				(2.09)	(1.97)
Intercept	-2.21	-3.04	-2.01	-3.41	-1.82	0.95	0.88	1.56	0.68	1.45
	(-0.93)	(-1.51)	(-1.01)	(-1.54)	(-0.76)	(0.59)	(0.56)	(0.99)	(0.41)	(0.93)
Number of observations	666	666	666	666	666	666	666	666	666	666
R-squared	0.019	0.013	0.020	0.027	0.052	0.003	0.013	0.018	0.013	0.031

Panel B. Using $WDLSI_{ETF\rightarrow Underlying}$

	Bid-ask spread					Amihud				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF_CAP	0.15	0.16	0.15	0.21	0.16	-0.09	-0.08	-0.09	-0.05	-0.06
	(0.99)	(1.22)	(0.98)	(1.36)	(0.98)	(-1.12)	(-0.89)	(-1.31)	(-0.59)	(-0.81)
ETF_VOLUME	-0.13*	-0.11	-0.13*	-0.13*	-0.15**	0.03	0.03	0.01	-0.09	-0.03
	(-1.86)	(-1.35)	(-1.75)	(-1.82)	(-2.13)	(0.81)	(0.85)	(0.31)	(-0.30)	(-0.89)
$SHORTRATE$	-0.67**				-0.29	-0.06				-0.21
	(-2.17)				(-0.78)	(-0.46)				(-1.11)

$TERMSPREAD$		0.31*			0.23		-0.11			-0.19
		(1.85)			(1.07)		(-1.29)			(-1.49)
$DEFAULTSPREAD$			0.53		0.66			0.44**		0.21
			(1.39)		(1.58)			(2.16)		(1.01)
YLD_STD				1.33	0.65				1.51**	1.36**
				(1.09)	(0.46)				(2.49)	(2.19)
Intercept	-0.93	-1.88	-1.21	-1.89	-0.62	1.04	0.81	1.41	0.61	1.39
	(-0.26)	(-0.56)	(-0.31)	(-0.57)	(-0.16)	(0.58)	(0.46)	(0.79)	(0.34)	(0.76)
Number of observations	666	666	666	666	666	666	666	666	666	666
R-squared	0.018	0.015	0.011	0.011	0.023	0.005	0.007	0.012	0.014	0.026

Panel C. Using $WDLSI_{Underlying \rightarrow ETF}$

	Bid-ask spread					Amihud				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF_CAP	-0.07	-0.02	-0.002	0.03	-0.06	-0.07	-0.07	-0.10	-0.06	-0.07
	(-0.61)	(-0.11)	(-0.03)	(0.21)	(-0.54)	(-0.99)	(-1.03)	(-1.34)	(-0.72)	(-1.05)
ETF_VOLUME	-0.06	-0.02	-0.02	-0.05	-0.62	0.05	0.05	0.02	0.04	-0.01
	(-1.23)	(-0.36)	(-0.45)	(-0.86)	(-1.34)	(1.55)	(1.43)	(0.65)	(0.97)	(-0.15)
$SHORTRATE$	-0.73***				-0.57*	0.12				-0.09
	(-2.96)				(-1.85)	(0.83)				(-0.46)
$TERMSPREAD$		0.56***			0.29		-0.29***			-0.28**
		(3.45)			(1.31)		(-3.54)			(-2.32)
$DEFAULTSPREAD$			0.12		0.29			0.64***		0.41**
			(0.41)		(0.98)			(3.51)		(1.98)
YLD_STD				0.91	0.32				0.68	0.59
				(0.87)	(0.29)				(1.12)	(0.99)
Intercept	1.29	0.17	0.09	-0.03	1.28	0.51	0.62	1.23	0.42	1.21
	(0.45)	(0.05)	(0.03)	(-0.01)	(0.43)	(0.27)	(0.36)	(0.69)	(0.22)	(0.73)
Number of observations	666	666	666	666	666	666	666	666	666	666
R-squared	0.022	0.016	0.0003	0.003	0.025	0.005	0.019	0.021	0.012	0.029

This table reports the regression results of the following regression models:

$$WLSI_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \quad (16)$$

$$WDLSI_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \quad (17)$$

where $WLSI_k$ and $WDLSI_k$ are the *Weekly Liquidity Spillover Index* and *Weekly Directional Liquidity Spillover Index* between the DIAMONDS ETF and its underlying portfolio using either the bid-ask spread or Amihud illiquidity ratio in week k, respectively. ETF_CAP_{k-1} and ETF_VOLUME_{k-1} are control variables in week $(k-1)$ ($Controls_{k-1}$). ETF_CAP_{k-1} is the logarithm of weekly average market capitalization of the ETF measured in million dollars. ETF_VOLUME_{k-1} is the logarithm of weekly average trading volume of the ETF measured in thousands of shares. $SHORTRATE_{k-1}$, $TERMSPREAD_{k-1}$, $DEFAULTSPREAD_{k-1}$, and YLD_STD_{k-1} are variables of interest in week $(k-1)$ ($Interest_{t-1}$). $SHORTRATE_{k-1}$ is the weekly change in the Federal Fund Rate. $TERMSPREAD_{k-1}$ is the weekly change in the difference between the yield on a constant maturity 10-year Treasury bond and the Federal Funds rate. $DEFAULTSPREAD_{k-1}$ is the weekly change in the difference between the yield on the Moody's Baa or better corporate bond yield index and the yield on a 10-year constant maturity Treasury bond. YLD_STD_{k-1} is the volatility of the Treasury note measured by its weekly standard deviation. The number in the parenthesis is the *t*-statistics of the parameter estimate. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7. Liquidity Spillover and Short Sale Constraints

	$WLSI_{i,Spread}$		$WLSI_{i,Amihud}$	
	(1)	(2)	(3)	(4)
$PILOT \times DURING$	0.14***	0.14***	0.21***	0.23***
	(3.34)	(3.34)	(4.14)	(4.14)
$PILOT \times POST$	-0.10**	-0.10**	-0.08	-0.07
	(-2.39)	(-2.39)	(-1.44)	(-1.44)
$PILOT$	-0.01	-0.01	0.02	0.02
	(-0.34)	(-0.34)	(0.44)	(0.44)
$DURING$	-0.06**	-0.06**	-0.04	-0.03
	(-2.00)	(-2.00)	(-0.97)	(-0.97)
$POST$	0.07**	0.07**	0.15***	0.14***
	(1.97)	(1.97)	(3.38)	(3.38)
$SIZE$	0.001	0.001	-0.05**	-0.05**
	(0.03)	(0.03)	(-2.23)	(-2.23)
STD	1.33*	1.33*	7.82***	7.82***
	(1.57)	(1.57)	(7.68)	(7.68)
$TURNOVER$	-0.01	-0.01	-0.12***	-0.12***
	(-0.83)	(-0.83)	(-4.53)	(-4.53)
$WEIGHT$	0.01	0.01	0.09**	0.09**
	(0.17)	(0.17)	(2.24)	(2.24)
Intercept	-0.05		0.39	
	(-0.23)		(1.48)	
Year-fixed Effects	No	No	No	No
Stock-fixed Effects	No	Yes	No	Yes
Number of observations	3,625	3,625	3,625	3,625
R-squared	0.011	0.011	0.029	0.032

The table above reports the regression results of the following equation:

$$WLSI_{i,k} = \alpha + \beta_1 PILOT_{i,k} \times DURING_{i,k} + \beta_2 PILOT_{i,k} \times POST_{i,k} + \beta_3 PILOT_{i,k} + \beta_4 DURING_{i,k} + \beta_5 POST_{i,k} + Controls_{i,k} + \varepsilon_k \quad (19)$$

where $WLSI_{i,k}$ is the *Weekly Liquidity Spillover Index* between component stock i with the DIAMONS ETF using either the bid-ask spread or Amihud illiquidity ratio as a liquidity measure in week k. $PILOT_{i,k}$ equals one if stock i is in the pilot group and zero otherwise. $DURING_{i,k}$ equals one if the weekly liquidity spillover index's end date is between Q3/2005 to Q2/2007 and zero otherwise. $POST_{i,k}$ equals one if the weekly liquidity spillover index's end date is between Q3/2007 to Q2/2009 and zero otherwise. $Controls_{i,k}$ is a set of control variables to consider the pilot and non-pilot stocks' trading characteristics including $SIZE_{i,k}$, $STD_{i,k}$, $TURNOVER_{i,k}$, and $WEIGHT_{i,k}$. $SIZE_{i,k}$ is the logarithm of weekly average of the stock market capitalization measured in thousands of dollars; $STD_{i,k}$ is the standard deviation of daily stock return in a week; $TURNOVER_{i,k}$ is the logarithm of weekly stock trading turnover measured in thousands of dollars; and $WEIGHT_{i,k}$ is the weight of stock i in the DIAMONDS ETF measured as in percentage. The number in the parenthesis is the *t*-statistics of the parameter estimate. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix A1. Liquidity of DIAMONDS ETF and the Underlying Portfolio

Figure A1.1 Bid-Ask Spread of the DIAMONDS ETF and the Underlying Portfolio

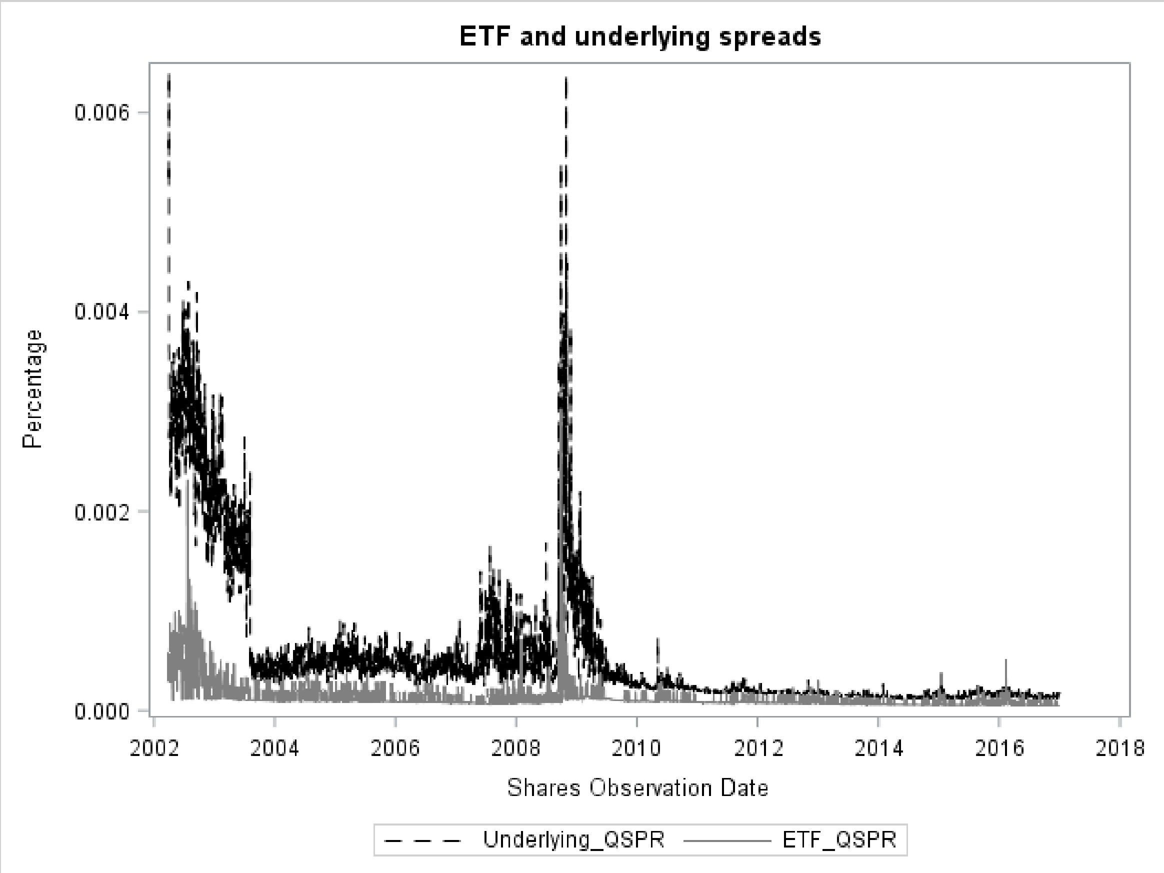
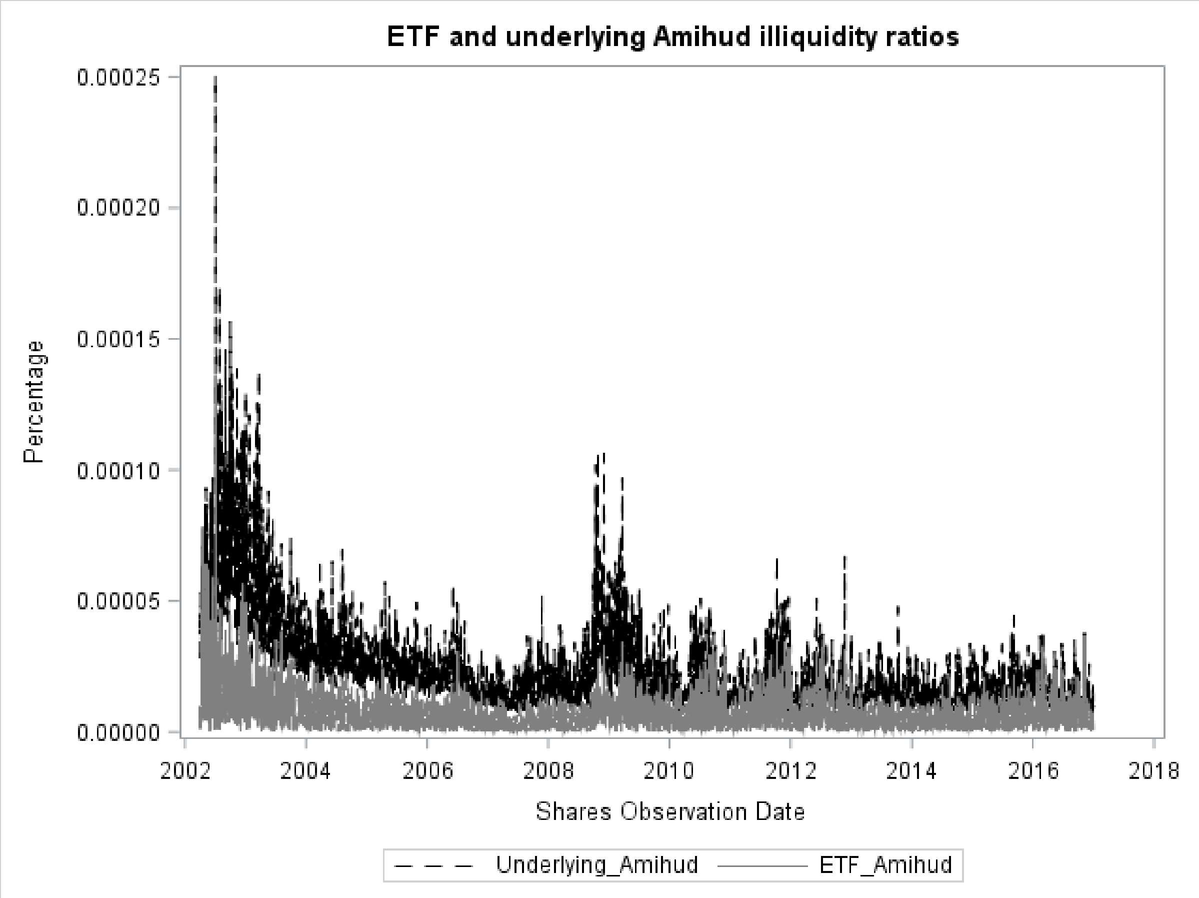


Figure A1.2 Amihud Illiquidity Ratio of the DIAMONDS ETF and the Underlying Portfolio



Figures A1.1 and A1.2 show the liquidity evolvement of the DIAMONDS ETF and its underlying portfolio over time. In Figure A1, liquidity is measured by the bid-ask spread and in Figure A2, liquidity is proxied by the Amihud illiquidity ratio. Liquidity of the underlying portfolio is the weighted average liquidity of the component stocks with the weights being the stocks' holding weights in the ETF. The sample period is from April 2002 to December 2016.

Appendix A2. Results of VAR Model of Individual Component Stocks of ETF

Stock Ticker	Bid-ask spread		Amihud	
	Test 1	Test 2	Test 1	Test 2
AA	149.3***	115.8***	32.0***	5.8*
AAPL	4.2	6.9**	1.9	5.3
AIG	2.7	11.5***	5.9*	12.8***
AXP	70.4***	151***	36.1***	4.1
BA	119.0***	164.3***	89.0***	8.1*
BAC	1.1	12.0***	7.1*	8.9**
C	88.3***	45.7***	9.6**	15***
CAT	51.4***	194.4***	84.2***	16.3***
CC	0.5	1.1	0.6	1.3
CSCO	8.4**	13.3***	1.4	0.3
CVX	11.4***	24.4***	10.5*	10.3*
DD	159.3***	195.9***	15.4***	36.3***
DIS	297.1***	151.4***	132.7***	15.6***
EK	9.9***	20.5***	7.6**	1.0
GE	117.7***	221.8***	54.2***	33.1***
GM	5.7*	12.0***	0.9	1.5
GS	2.9	6.7*	1.5	3.2
HON	80.8***	55.4***	24.1***	8.6**
HD	201.2***	146.1***	60.0***	20.9***
HPQ	83.4***	130.8***	59.9***	20.8***
IBM	73.4***	129.1***	19.4***	23.1***
INTC	8.0**	11.0**	29.3***	8.3*
IP	38.1***	5.4	0.8	0.6
JNJ	40.1***	138.6***	64.2***	45.4***
JPM	44.7***	134.8***	99.8***	22.5***
KO	369.2***	227.5***	51.1***	36.2***
MCD	130.7***	140.8***	65.2***	13.8***
MDLZ	9.3**	60.1***	0.8	2.0
MMM	54.7***	197.1***	2.3	4.4
MO	73.8***	110.0***	13.5***	30.7***
MRK	17.6***	77.0***	39.4***	21.3***
MSFT	1.8	3.3	5.6*	8.9***
NKE	6.3*	7.3*	4.3	12.7***
PFE	53.8***	43.4***	39.2***	42.2***
PG	78.3***	139.4***	44.8***	34.3***
T	110.7***	203.2***	101.2***	8.8*
TRV	3.3	7.5**	4.9	12.6***
UNH	30.6***	24.2***	4.6	2.8
UTX	83***	150.6***	81.7***	29.6***
V	7.9***	2.9	24.1***	9.6*
VZ	31.9***	28.4***	0.7	4.7
WMT	90.5***	173.2***	98.4***	66.2***

XOM	54.5***	283.8***	103.2***	9.6**

This table reports the Chi-square statistics of pairwise Granger causality tests between the endogenous variables in the VAR model:

$$ETF_t = \sum_{j=1}^{k} \beta_j ETF_{t-j} + \sum_{j=1}^{k} \gamma_j Stock_{i,t-j} + \varepsilon_t \quad \text{(A1)}$$

$$Stock_{i,t} = \sum_{j=1}^{k} \mu_j Stock_{i,t-j} + \sum_{j=1}^{k} \lambda_j ETF_{t-j} + \phi_t \quad \text{(A2)}$$

where ETF and $Stock$ are vectors representing daily values of liquidity, return, and volatility of the DIAMONDS ETF and those of the individual constituent stock, respectively. The above VAR system includes a 6-equation vector autoregression specification that incorporates six variables: three for the ETF (liquidity: $LIQ_{E,t}$, return: $RET_{E,t}$, and volatility: $VOL_{E,t}$) and three for the underlying stock (liquidity: $LIQ_{S,i,t}$, return: $RET_{S,i,t}$, and volatility: $VOL_{S,i,t}$). Liquidity can be proxied by either the quoted bid-ask spread ($QSPR_{E,t}$ and $QSPR_{S,i,t}$) or Amihud illiquidity ratio ($Amihud_{E,t}$ and $Amihud_{S,i,t}$). Lag lengths are selected based on the AIC. In Test 1, the null hypothesis is the ETF liquidity is influenced by itself but not underlying stock liquidity. In Test 2, the null hypothesis is the underlying stock liquidity is influenced by itself but not ETF liquidity. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix A3. Granger Causality Tests with Exogenous Variables

Panel A. Using quoted bid-ask spread as liquidity measure

	$QSPR_E$	VOL_E	RET_E	$QSPR_U$	VOL_U	RET_U
$QSPR_E$		14.8	14.2	16.5	7.3	17.4
		(0.0050)	(0.0070)	(0.003)	(0.1200)	(0.0020)
VOL_E	103.1		9.4	19.6	24.3	9.6
	(0.0001)		(0.0500)	(0.0006)	(0.0001)	(0.0500)
RET_E	24.2	288.6		27.0	257.5	0.8
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.9400)
$QSPR_U$	287.1	45.8	15.5		49.0	19.5
	(0.0001)	(0.0001)	(0.0040)		(0.0001)	(0.0001)
VOL_U	106.5	55.4	18.4	11.4		18.1
	(0.0001)	(0.0001)	(0.0010)	(0.0300)		(0.0010)
RET_U	22.1	291.2	5.2	28.4	252.5	
	(0.0002)	(0.0001)	(0.2900)	(0.0001)	(0.0001)	

Panel B. Using Amihud illiquidity as liquidity measure

	$Amihud_E$	VOL_E	RET_E	$Amihud_U$	VOL_U	RET_U
$Amihud_E$		37.1	6.2	45.1	18.2	5.9
		(0.0001)	(0.1800)	(0.0010)	(0.0010)	(0.2000)
VOL_E	128.1		9.4	142.1	24.3	9.6
	(0.0001)		(0.0500)	(0.0001)	(0.0001)	(0.0500)
RET_E	55.6	288.6		98.9	257.5	0.8
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.9400)
$Amihud_U$	54.8	32.9	11.6		22.0	11.7
	(0.0010)	(0.0010)	(0.0200)		(0.0010)	(0.0200)
VOL_U	108.6	55.4	18.4	115.8		18.1
	(0.0001)	(0.0001)	(0.0010)	(0.0001)		(0.0010)
RET_U	51.7	291.2	5.2	92.6	252.5	
	(0.0001)	(0.0001)	(0.2700)	(0.0001)	(0.0001)	

This table reports the Chi-square statistics and p-values (in parenthesis) of pairwise Granger causality tests between the endogenous variables in the VAR model:

$$X_t = \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + VIX_t + MDT_t + \varepsilon_t \quad \text{(A3)}$$

$$Y_t = \sum_{j=1}^{k} \mu_j Y_{t-j} + \sum_{j=1}^{k} \lambda_j X_{t-j} + VIX_t + MDT_t + \phi_t \quad \text{(A4)}$$

where *X* and *Y* are vectors representing liquidity, return, and volatility of the DIAMONDS ETF and those of the underlying portfolio, respectively. The above VAR system includes a 6-equation vector autoregression specification that incorporates six endogenous variables: three for the ETF (liquidity: $LIQ_{E,t}$, return: $RET_{E,t}$, and volatility: $VOL_{E,t}$) and three for the underlying portfolio (liquidity: $LIQ_{U,t}$, return: $RET_{U,t}$, and volatility: $VOL_{U,t}$). Liquidity can be proxied by either the quoted bid-ask spread ($QSRP_{E,t}$ and $QSPR_{U,t}$) or Amihud illiquidity ratio ($Amihud_{E,t}$ and $Amihud_{U,t}$). The null hypothesis is that a row variable does not Granger-cause a column variable. VIX_t is the volatility of the S&P500 index and MDT_t is the dollar trading volume of the S&P500 index measured in USD million.

Appendix A4. Granger Causality Tests with Modified Amihud Illiquidity

	MOD_AMI_E	VOL_E	RET_E	MOD_AMI_U	VOL_U	RET_U
MOD_AMI_E		43.0	16.0	19.6	33.6	15.0
		(0.0001)	(0.1000)	(0.0300)	(0.0002)	(0.1300)
VOL_E	37.8		14.9	18.6	31	10.9
	(0.0001)		(0.1400)	(0.0500)	(0.0001)	(0.3600)
RET_E	60.0	339.8		89.4	298.4	21.1
	(0.0001)	(0.0001)		(0.0010)	(0.0001)	(0.2000)
MOD_AMI_U	48.7	36.4	10.8		29.6	10.5
	(0.0001)	(0.0001)	(0.3700)		(0.0010)	(0.3900)
VOL_U	37.9	42.7	32.9	18.7		30.4
	(0.0001)	(0.0001)	(0.0003)	(0.0500)		(0.0001)
RET_U	58.2	343.4	23.4	87.3	292.3	
	(0.0001)	(0.0001)	(0.1500)	(0.0001)	(0.0001)	

This table reports the Chi-square statistics and p-values (in parenthesis) of pairwise Granger causality tests between the endogenous variables in the VAR model:

$$X_t = \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + \varepsilon_t \quad \text{(A5)}$$

$$Y_t = \sum_{j=1}^{k} \mu_j Y_{t-j} + \sum_{j=1}^{k} \lambda_j X_{t-j} + \phi_t \quad \text{(A6)}$$

where X and Y are vectors representing daily values liquidity, return, and volatility of the DIAMONDS ETF and those of the underlying portfolio, respectively. The above VAR system includes a 6-equation vector autoregression specification that incorporates six variables: three for the ETF (liquidity: $LIQ_{E,t}$, return: $RET_{E,t}$, and volatility: $VOL_{E,t}$) and three for the underlying portfolio (liquidity: $LIQ_{U,t}$, return: $RET_{U,t}$, and volatility: $VOL_{U,t}$). Liquidity can be proxied by either the quoted bid-ask spread ($QSPR_{E,t}$ and $QSPR_{U,t}$) or modified Amihud illiquidity ratio ($MOD\_AMI_{E,t}$ and $MOD\_AMI_{U,t}$). MOD_AMI is calculated using methodology proposed by Florackis et al. (2011). The null hypothesis is that a row variable does not Granger-cause a column variable.

Appendix A5. Summary of Dependent Variables in Section 4

Variables	Mean	Median	Std.Dev	Min	Max
ETF_CAP	944	903	2,180	552	14,780
ETF_VOLUME	9,084	6,959	6,954	2,017	62,490
PMI_D	0.106	0	0.308	0	1
MKT_RET	0.15	0.26	2.39	-20.08	10.17
MKT_STD	0.96	0.73	0.80	0.06	7.86
PCR	0.64	0.64	0.09	0.41	1.01
HLR	14.95	6.08	26.65	0.01	344.30
$SHORTRATE$	-0.0012	0.0001	0.0981	-1.0812	0.3535
$TERMSPREAD$	-0.0011	-0.0100	0.1652	-0.7941	1.3934
$DEFAULTSPREAD$	-0.0024	0.0013	0.0871	-0.5231	0.7415
YLD_STD	0.0240	0.0150	0.0270	0	0.2140

This table reports the descriptive statistics of the dependent variables used in Section 4. The definitions and calculations of these variables are presented in Section 4.

Appendix A6. Test for Reverse Causality

Panel A. Using bid-ask spread as proxy for liquidity

	ABS_FUND_FLOW				PRC_ERR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF_CAP	-1.88	-1.73	-1.45	-1.31	-75.10***	-73.02***	-72.92	78.26***
	(-0.54)	(-0.50)	(-0.42)	(0.38)	(-11.98)	(-10.60)	(-10.83)	(-12.45)
ETF_VOLUME	7.69	7.81***	7.89***	8.35***	38.11***	38.51***	38.81	33.06***
	(4.97)	(5.14)	(5.18)	(5.38)	(7.83)	(7.20)	(7.00)	(7.70)
$WLSI$	0.002			-0.005	0.01			0.08
	(1.27)			(-1.19)	(1.52)			(1.18)
$WDLSI_{ETF \rightarrow Underlying}$		0.001		0.004		-0.0004		-0.04
		(0.91)		(1.40)		(-0.09)		(-1.48)
$WDLSI_{Underlying \rightarrow ETF}$			0.002	0.005			0.01	-0.03
			(1.46)	(1.36)			(0.87)	(-1.47)
Intercept			0.01*	0.01*	0.09***	0.09***	0.09***	0.09***
			(1.79)	(1.71)	(10.72)	(8.80)	(9.19)	(11.42)
Number of observations	666	666	666	666	666	666	666	666
R-squared	0.086	0.083	0.088	0.089	0.447	0.432	0.434	0.497

Panel B. Using Amihud illiquidity as proxy for liquidity

	ABS_FUND_FLOW				PRC_ERR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF_CAP	-1.36	-1.38	-1.44	-1.27	-72.73***	-73.08***	-72.59***	-72.48***
	(-0.39)	(-0.40)	(-0.41)	(-0.37)	(-10.75)	(-10.97)	(-10.68)	(-10.63)
ETF_VOLUME	7.78	7.79***	7.75***	7.92***	38.57***	38.53***	38.49***	38.71***
	(5.15)	(5.10)	(5.18)	(5.10)	(7.11)	(7.09)	(7.14)	(7.02)

$WLSI$	0.002			0.02	0.004			0.07
	(0.62)			(0.91)	(0.65)			(1.03)
$WDLSI_{ETF \rightarrow Underlying}$		0.002		-0.01		0.0003		-0.04
		(0.67)		(-0.77)		(0.07)		(-1.20)
$WDLSI_{Underlying \rightarrow ETF}$			0.001	-0.01			0.01	-0.02
			(0.43)	(-0.88)			(0.84)	(-0.66)
Intercept	0.01^{*}	0.01^{*}	0.01^{*}	0.01^{*}	0.08^{***}	0.09^{***}	0.09^{***}	0.09^{***}
	(1.73)	(1.74)	(1.76)	(1.68)	(9.05)	(9.15)	(9.08)	(8.97)
Number of observations	666	666	666	666	666	666	666	666
R-squared	0.083	0.083	0.082	0.081	0.432	0.432	0.433	0.434

This table reports the regression results of the following regression models:

$$ABS\_FUND\_FLOW_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \quad \text{(A7)}$$

$$PRC\_ERR_k = \alpha + Controls_{k-1} + Interests_{k-1} + \varepsilon_k \quad \text{(A8)}$$

where $ABS\_FUND\_FLOW_k$ is the average of the daily percentage absolute change in fund inflow or outflow of the ETF in one week. PRC_ERR_k is the average pricing error of the ETF for one week. Daily pricing error is measured as the absolute value of ETF premium or discount. ETF_CAP_{k-1} and ETF_VOLUME_{k-1} are control variables in week $(k-1)$ (*Controls*$_{k-1}$). ETF_CAP_{k-1} is the logarithm of weekly average market capitalization of the ETF measured in million dollars. ETF_VOLUME_{k-1} is the logarithm of weekly average trading volume of the ETF measured in thousands of shares. $WLSI_{k-1}$ and $WDLSI_{k-1}$ are variables of interest in week $(k-1)$ (*Interest*$_{k-1}$). $WLSI_{k-1}$ and $WDLSI_{k-1}$ are the *Weekly Liquidity Spillover Index* and *Weekly Directional Liquidity Spillover Index* between the DIAMONDS ETF and its underlying portfolio using either the bid-ask spread or Amihud illiquidity ratio, respectively. The reported coefficients of ETF_CAP_{k-1} and ETF_VOLUME_{k-1} are multiplied by 10^{13} and 10^{10}, respectively. The number in the parenthesis is the *t*-statistics of the parameter estimate. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix A7. Stock-level Determinants of Liquidity Spillover

	$WLSI_{i,Spread}$				$WLSI_{i,Amihud}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SIZE$	0.003	0.12*	0.02	0.17**	-0.002	0.09***	-0.03***	0.06***
	(0.14)	(1.68)	(0.91)	(2.15)	(-0.25)	(6.21)	(-4.14)	(2.96)
STD	5.55***	6.93***	5.38***	6.89***	9.12***	10.67***	10.58***	11.97***
	(2.93)	(3.51)	(2.75)	(3.32)	(18.67)	(20.15)	(20.21)	(21.35)
$TURNOVER$	-0.11**	-0.12**	-0.06	-0.08	-0.14***	-0.16***	-0.20***	-0.25***
	(-2.25)	(-2.19)	(-1.37)	(-1.29)	(-12.37)	(-12.28)	(-14.01)	(-14.99)
$WEIGHT$	0.01	-0.03	0.01	-0.04	0.01	-0.02**	0.02***	-0.02*
	(0.61)	(-0.87)	(0.52)	(-1.20)	(1.56)	(-2.08)	(3.54)	(-1.87)
Intercept	-0.14				0.31			
	(-0.43)				(0.29)			
Year-fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Stock-fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	20,210	20,210	20,210	20,210	20,210	20,210	20,210	20,210
R-squared	0.011	0.012	0.015	0.021	0.022	0.027	0.039	0.042

This table reports the regression results of the following equation:

$$WLSI_{i,k} = \alpha + \beta_1 SIZE_{i,k-1} + \beta_2 STD_{i,k-1} + \beta_3 TURNOVER_{i,k-1} + \beta_4 WEIGHT_{i,k-1} + \varepsilon_k \quad \text{(A9)}$$

where $WLSI_{i,k}$ is the *Weekly Liquidity Spillover Index* between component stock i with the DIAMONDS ETF using the bid-ask spread or Amihud illiquidity ratio as liquidity measure in week k. $SIZE_{i,k-1}$ is the logarithm of the weekly average of the stock market capitalization measured in thousands of dollars. $STD_{i,k-1}$ is the standard deviation of daily stock return in a week. $TURNOVER_{i,k-1}$ is the logarithm of weekly stock trading turnover measured in thousands of dollars. $WEIGHT_{i,k-1}$ is the weight of stock i in the ETF measured in percentage. Dependent variables are measured in week $(k-1)$. The number in the parenthesis is the *t*-statistics of the parameter estimate. ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.