Essays on Portfolio Liquidity

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ABSTRACT

Prior research focuses on the liquidity of individual assets such as stocks, bonds, etc. In more recent times, with the robust growth of basket products such as exchange-traded funds (ETFs) or futures, researchers have shifted their attention to the liquidity of a portfolio of assets. When being traded on a stock exchange, a portfolio incurs trading costs like stock. However, unlike stock, the market liquidity of a portfolio is affected by its degree of diversification and pricing error. This thesis consists of three essays and contributes to the literature on portfolio liquidity. Essay One investigates the market liquidity of active ETF, a renovated and fast-growing basket product. Essay Two examines the extent to which transaction costs in trading ETFs can be minimized via a systematic trading schedule. Finally, essay Three studies the spillover between the market liquidity of an ETF and the liquidity of its underlying stocks.

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CHAPTER ONE: INTRODUCTION

This chapter provides an overview of this thesis. It discusses the motivation for investigating the portfolio's liquidity and the contribution of each of the three essays contained in the thesis. The chapter concludes by outlining a structure for the remainder of the thesis.

1.1. Introduction

Liquidity is a crucial dimension of financial markets. The ability to buy or sell an asset in a timely, low-cost manner impacts the pricing of assets and market stability. Many studies (Amihud and Mendelson, 1986; Bradrania, Peat, and Satchell, 2015; Lam and Tam, 2011) have emphasized the significant relationship between market liquidity and stock returns. Stock market liquidity is of prime importance even to the economy. Ellington (2018) notes that lower market liquidity negatively dampens economic growth during a period of crisis. Furthermore, Naes, Skjeltorp, and Odegaard (2011) consider market liquidity a relevant parameter in forecasting the future state of the economy. Liquidity research is therefore essential to academics, practitioners, and regulators.

Most of the early studies emphasize the liquidity of individual assets such as stocks, bonds, etc. In more recent times, the tremendous development of basket products such as exchange-traded funds (ETFs) or futures has diverted the attention of researchers to the liquidity of a portfolio of assets. As a portfolio of assets can be traded on an exchange, it shares many liquidity characteristics with stocks. However, while a stock faces significant firm-level risk, a portfolio is usually diversified. Thus, the role of diversification in determining portfolio liquidity is crucial. Subrahmanyam (1991), Gorton and Pennacchi (1993) argue that a portfolio would have less adverse selection costs than stocks because of being diversified. As a result, they predict the market liquidity should be greater than that of the underlying stocks.

This thesis consists of three essays and contributes to the literature on portfolio liquidity. The first essay studies the market liquidity of active ETFs - a renovated basket product with robust growth in recent years. Essay Two examines ETF intraday bid-ask spread predictability and investigates different trading strategies to minimize ETF spread costs. Finally, essay Three studies the liquidity spillover between the market liquidity of an ETF and the liquidity of its underlying stocks.

The remainder of this chapter proceeds as follows. The following three sections (Section 1.2, 1.3, and 1.4) provide an overview, including the important contribution to the existing literature, of each of the three essays. Section 1.5 presents the research output from this thesis, and the structure of the remainder of the thesis is contained in Section 1.6.

1.2. Essay One

The first essay investigates the market liquidity of active ETFs, a relatively new product in the investment industry. Both passive and active ETFs share many common features, such as product structure and regulation. However, they have some unique aspects that could affect their liquidity differently. For example, passive ETFs can track a specific market index, whereas active ETFs aim to outperform the market. Moreover, active ETF managers have their discretion over portfolio management, which leads to the uncertainty of future ETF portfolio composition. The uncertainty of portfolio composition could be a crucial determinant of active ETF liquidity for two important reasons. First, it could impair the arbitrage mechanism of active ETFs. Because market makers are more uncertain about the portfolio composition, they are more reluctant to arbitrage away the pricing errors of active ETFs. For example, Thirumalai (2003) finds that in Germany, the pricing errors of active ETFs are higher than those of passive ETFs. Second, the adverse selection costs of a portfolio positively correlated with the uncertainty of the portfolio's investment policy

(Clarke and Shastri, 2001). As a result, the uncertainty of the future composition of an active ETF portfolio could indicate more adverse selection costs borne by its investors.

Using a sample of active US active ETFs, Essay One finds that active ETF liquidity is significantly lower than the weighted average liquidity of its underlying portfolio. This finding is a puzzle given the current literature on trading stock baskets and relative liquidity of passive ETFs (Subrahmanyam, 1991; Hedge and McDermott, 2004; Marshall, Nguyen, and Visaltanachoti, 2018; Broman and Shum, 2018). However, this finding is consistent with our conjecture that the uncertainty of future holdings could be a crucial determinant of adverse selection costs borne by active ETF investors. Consequently, active ETF liquidity may be lower than its underlying liquidity in comparison with passive ETF liquidity. Furthermore, the essay documents a negative correlation between ETF liquidity and its degree of diversification. It shows a trade-off between a portfolio's diversification and the liquidity of its underlying stocks. These findings are consistent with Pastor, Stambaugh, and Taylor's (2017) argument that these two characteristics are substitutes, and a more diversified portfolio tends to invest more in illiquid stocks. Underlying liquidity transmits to ETF liquidity through the creation/redemption mechanism. As a result, ETF liquidity can suffer the negative effect of diversification. The above channels could explain our empirical finding of an inverse relationship between ETF diversification and its liquidity.

This essay contributes to the existing literature in several ways. First, this is the first to study the liquidity of active ETFs. Second, we extend the theoretical work of Pastor and Stambaugh (2017) to investigate the impact of portfolio diversification on portfolio liquidity empirically. Finally, the essay contributes to understanding determinants of the discrepancy between ETF liquidity and underlying liquidity. While this discrepancy is documented in the literature, it is not yet explained. The essay suggests that this liquidity mismatch is driven by the difference in trading characteristics of ETFs and their underlying stocks and by portfolio-specific characteristics.

1.3. Essay Two

The second essay considers the extent to which transaction costs in trading ETFs can be minimized via a systematic trading schedule. This is an important topic for several reasons. First, ETFs are an important and growing component of financial trading that attracts many high-frequency traders. Second, while ETF spreads tend to be lower than stocks, they are widely diverse. Third, although investors can choose to invest in ETFs with the lowest bid-ask spreads, these ETFs tend to charge higher management fees (Khomyn, Putniņš, and Zoican, 2020).

Using an unrestricted vector autoregressive (VAR) model for a large sample of 1,350 US ETFs between January 2011 and December 2017, we find that this model is superior to a moving average model in predicting short-term ETF bid-ask spreads. Moreover, splitting and timing trades based on predictions from this model reduce transaction costs considerably for large ETF traders compared to other trading schedules. The average executed bid-ask spread using the VAR model to schedule trade is 7.4% and 8.29% lower than that using a naïve trading schedule and a moving average trading schedule, respectively. The spread discount for a large ETF trader using the VAR trading schedule is as high as 30.81% compared to ETFs' daily average bid-ask spread. However, for a retail ETF trader who does not need to split his order, we reveal that trading once at the close would be optimal to reduce bid-ask spread cost.

This essay makes several contributions to the current literature on portfolio liquidity. First, to the best of my knowledge, the essay is dedicated to predicting ETF liquidity. Second, it examines the degree to which ETF transaction costs can be saved using ETF bid-ask spread predictions, which have not been documented in the literature. Third, the essay also points out the effect of spread volatility on the extent to which scheduling trades can save transaction costs.

1.4. Essay Three

An ETF is widely promoted as having two layers of liquidity, its market liquidity and the liquidity of its underlying portfolio. However, recent market "flash crashes" have questioned the resilience of ETF liquidity as its market liquidity and its underlying liquidity can dry up simultaneously. The third essay is the first attempt to document the magnitude and determinants of liquidity spillover between an ETF and its underlying portfolio.

Using daily data of DIAMONDS ETF on the Dow Jones Industrial Average and its underlying stocks from April 2002 to December 2016, the paper finds significant liquidity spillover between the ETF and its underlying portfolio. The report reveals that liquidity shocks from the underlying stocks significantly affect the ETF liquidity than in reverse. The results are consistent by using both bid-ask spread and Amihud illiquidity as liquidity proxies. Moreover, Essay Three also investigates market-level determinants of the liquidity spillover between the ETF and its underlying portfolio. The essay shows that the liquidity spillover is greater during market crises, economic downturns, and high volatility. These findings align with the "wealth effect" theory of financial contagion (Kyle and Xiong, 2012), which posits that rising risk aversion in the market increases liquidity spillover among asset classes. The paper also examines the effect of funding costs and short-sale constraints, two main drivers of ETF arbitrage, on liquidity spillover. The paper finds that the impact of funding costs on liquidity spillover differs depending on the component of funding costs. A rise in short-term rate decreases the liquidity spillover, while an uptick in default spread increases the liquidity spillover. Finally, the paper shows that the liquidity spillover between an ETF and its underlying portfolio is higher when short sale restrictions loosen.

Essay Three contributes to the literature of portfolio liquidity in several ways. First, it directly addresses a growing concern from both investors and regulators about the simultaneous dry-ups of liquidity in financial markets. Second, built on the literature on liquidity spillover and financial contagion, the essay comprehensively analyzes market-level determinants of liquidity spillover. Third, the negative impact of short sale restrictions on liquidity spillover between ETF and component stock documented in the paper is novel. More importantly, it gives a reason for financial market regulators to use a short sale ban to reduce the contagion effect during the time of market crisis.

1.5. Research outputs from the thesis

Essay One, "The liquidity of active ETFs", was published in the following journal:

Son D.P., Ben, R.M., Nhut, H.N., and Nuttawat, V. (2020). The liquidity of active ETFs. *Global Finance Journal (In Press).* https://doi.org/10.1016/j.gfj.2020.100572.

Moreover, this essay has been presented at

- The 2019 Asian Finance Association Conference in Ho Chi Minh City (2019)
- School of Economics and Finance Seminar at Massey University (2019)

Essay Two, "*Predicting ETF liquidity*", has been submitted to the *Financial Analysts Journal* and in waiting for the journal's decision.

Essay Three, "*Liquidity spillover between ETFs and their constituents*", has been re-submitted to the *International Review of Financial Analysis* after conducting revision following the journal's review.

1.6. Structure of the thesis

The remainder of the thesis is organized as follows. Chapter 2 contains the first essay investigating the liquidity of active ETFs. The second essay on the predictability of ETF liquidity is presented in Chapter 3. Chapter 4 presents the third essay on the liquidity spillover between an ETF and its underlying portfolio. Chapter 5 concludes the thesis by outlining the significant findings and implications of each of the three essays.

CHAPTER TWO: ESSAY ONE

This chapter presents the first essay, which investigates the market liquidity of active ETFs, using data of 23 US active equity ETFs over the 2011-2017 period. A brief overview of the key findings is presented in Section 2.1. Section 2.2 reviews related literature. Section 2.3 presents the data. Section 2.4 reports the core results and related discussion. Section 2.5 concludes this chapter. An appendix to this chapter and the essay’s reference list are provided at the thesis's end.

The liquidity of active ETFs

ABSTRACT

Active exchange traded funds (ETFs) are less liquid than their underlying portfolios. We attribute this finding, which contrasts with that for passive ETFs, to uncertainty about the future holdings of active ETFs. In addition, while diversification generally reduces firm-specific information asymmetry and improves portfolio liquidity, it impairs the liquidity of active ETFs, consistently with the substitution effect between diversification and liquidity documented in the literature. We show that the gap between active ETF and underlying liquidity varies cross-sectionally and over time and can be explained by differences in size and volume between ETFs and their underlying portfolio, by ETF age, and by ETF pricing errors.

JEL classifications*:* G11, G23
Keywords*:* ETFs, Portfolio liquidity, Diversification

2.1. Introduction

We examine differences in liquidity between active exchange traded funds (ETFs) and their underlying portfolios and what factors determine these differences. Active ETFs are a relatively new product in the investment industry. The first U.S. active ETF, the Bear Stearns Current Yield Fund, was launched in 2008, fifteen years later than the birth of the first passive U.S. ETF.[1] Although passive ETFs still dominate the ETF industry, accounting for 98% of industry assets under management (AUM), active ETFs have experienced impressive growth. Compared to mutual funds, active ETFs provide investors with a relatively liquid and convenient way to employ alpha-generating strategies, as they offer intraday liquidity, tax efficiency, and lower fees. As of September 2019, the global active ETF market has garnered about USD 141 billion in AUM, for

[1] The first U.S. ETF, the SPDR S&P 500 ETF, dates from January 23, 1993.

a compound annual growth rate of 169% since 2009 (Fuhr, 2019). Ernst & Young (2017) predicts that AUMs of active ETFs could grow to USD 217 billion in 2020.

Despite the growing popularity of active ETFs, little is known about their liquidity. Most studies of ETF liquidity focus on passive ETFs (Broman andand Shum, 2018; Calamia, Deville, andand Riva, 2016; Hedge andand McDermott, 2004). While sharing many common characteristics such as product structure and regulation, passive and active ETFs have some differences that could affect their liquidity. Passive ETFs are designed to track a specific market index, whereas active ETFs aim to outperform the market. Moreover, even though both active and passive ETFs in the United States are required to disclose their holdings daily,[2] the discretion of active ETF managers over portfolio management leads to uncertainty about future ETF portfolio composition. This uncertainty could harm the ability of active ETF market makers to arbitrage efficiently and increase the fund's adverse selection cost (see Clarke andand Shastri, 2001).

Theoretical models predict that ETF liquidity should be greater than underlying liquidity (Gorton andand Pennacchi, 1993; Subrahmanyam, 1991). As security-specific information asymmetry is lessened in a stock basket, the basket becomes a preferred trading medium for liquidity traders and has lower transaction costs than its underlying stocks. Accordingly, Hedge and McDermott (2004), Marshall, Nguyen, and Visaltanachoti (2018), and Broman and Shum (2018) find that passive ETF liquidity is higher than underlying liquidity. However, for active ETFs, adverse selection costs could make the fund's liquidity lower than that of its underlying stocks. Using a sample of U.S. active ETFs, we compare their liquidity with that of the underlying stocks.

[2] In December 2020, the U.S. Securities Commission approved four actively managed ETFs that do not disclose their holdings daily.

We also examine the relationship between an ETF's liquidity and its degree of diversification. Subrahmanyam (1991) and Gorton and Pennacchi (1993) have documented that diversification reduces a portfolio's information asymmetry borne by market makers and thus increases its liquidity. However, diversification has a decreasing marginal benefit[3] and its own cost dimension. Hamm (2014) hypothesizes a feedback loop to explain how diversification can reduce an ETF's liquidity. Pastor, Stambaugh, and Taylor (2020) document a trade-off between a portfolio's diversification and the liquidity of its underlying stocks and argue that a more diversified portfolio tends to invest more in illiquid stocks. Underlying liquidity is transmitted to ETF liquidity through the creation/redemption mechanism. As a result, diversification may harm the ETF's liquidity. To examine this possibility, we use three different proxies for diversification.

We also investigate factors that may affect the gap between ETF and underlying liquidity. First, when an ETF is traded on the market, it has its own trading volume, return volatility, market capitalization, and market price. These trading characteristics reflect both inventory costs and the information asymmetry of the traded security (Stoll, 2000; Van Ness, Van Ness, andand Warr, 2001). In particular, we look at discrepancies in market capitalization and trading volume between an ETF and its underlying stocks.

Second, ETFs have distinct characteristics that stocks do not possess. One of these characteristics is ETF pricing error, measured by the absolute difference between an ETF's net asset value (NAV) and its market price. According to Rompotis (2012), the pricing error of an ETF could signal the inefficiency of its creation/redemption mechanism or its operational risk and

[3] Evans and Archer (1968) show that the relationship between the number of stocks in a portfolio and the portfolio's return dispersion takes the form of a rapidly decreasing asymptotic function, with the asymptote approximating the level of systematic variation in the market.

consequently lower its market liquidity. As the pricing error can affect ETF liquidity, it could explain the difference between ETF liquidity and underlying liquidity.

We consider active ETFs an ideal laboratory to study the impact of portfolio diversification on portfolio liquidity, on both cross-sectional and time-series bases. Although different passive ETFs can have different degrees of portfolio diversification, these are normally determined by the diversification of the tracking indices. For instance, the Dow Jones Industrial Average has 30 component stocks. This number is kept stable over time, so passive ETFs tracking this index will have 30 corresponding holdings over time. A very rough measure of diversification as the number of holdings hence remains constant. For active ETFs, fund sponsors or managers do not need to track any index; therefore, they are free to choose the level of diversification for their portfolio.

Our research contributes to current literature on portfolio liquidity in three ways. First, to the best of our knowledge, we are the first to study the liquidity of active ETFs. Second, by investigating the impact of portfolio diversification on portfolio liquidity, we challenge the common assumption that diversification benefits ETF investors, and contribute to the scarce literature on the risks of diversification. Third, we investigate not only the existence but also the determinants of the discrepancy between ETF liquidity and underlying liquidity. Hedge and McDermott (2004), Marshall et al. (2018), and Broman and Shum (2018) point out the difference between ETF and underlying liquidity, but they do not explain it.

The remainder of this paper is structured as follows. Section 2.2 reviews related literature and develops hypotheses. Section 2.3 describes our data. Section 2.4 documents the empirical results of testing the hypotheses developed in section 2.2. Section 2.5 concludes the paper.

2.2. Literature review and hypotheses development

2.2.1. *Magnitude difference between active ETF liquidity and underlying liquidity*

Extant theories predict that a traded portfolio should have more liquidity than the weighted average liquidity of its underlying stocks because it has a lower adverse selection cost. Subrahmanyam (1991) models the interaction between informed traders and liquidity traders when they can choose to trade in either the market for the basket or the market for the underlying securities. He concludes that markets for baskets of securities are cheaper to trade in than those for individual securities. In a similar vein, Gorton and Pennachi (1993) argue that a composite security appeals to uninformed traders more than its underlying stocks do, as trading the composite security decreases their expected loss to informed traders.

These theories have been tested for both closed-end funds and ETFs. Neal and Wheatley (1998) find that the adverse selection component of closed-end funds' bid-ask spreads is surprisingly high given those funds' transparency and diversification. By contrast, Clarke and Shastri (2001) and Chen, Jiang, Kim, and McInish (2003) find that both the spread and the adverse selection component of closed-end funds are lower than those of their matched sample of common stocks. Hedge and McDermott (2004) compare the effective spreads and their components of two ETFs, namely the DIAMONDS (tracking the Dow Jones Industrial Average) and the Q's (tracking the NASDAQ 100 Index), with those of the corresponding underlying stock baskets. They find that the DIAMONDS is more liquid than its underlying stock basket, and this superior liquidity largely stems from lower adverse selection costs of trading. Marshall et al. (2018) find a similar result: the effective spread on the Dow Jones Industrial Average ETF (DIA) is lower than the price-weighted effective spread of the underlying stocks. Moreover, Broman and Shum (2018) find that

ETFs are, on average, 5% more liquid than their underlying stock baskets.[4] These studies, however, cover only passive ETFs.

For active ETFs, portfolio managers have greater discretion over portfolio construction, and we expect that this active management reduces liquidity, for at least two reasons. First, active management increases inventory cost for active ETF market makers, as it becomes more difficult for them to arbitrage efficiently when they face uncertainty about the ETF's future portfolio composition. Thirumalai (2003) finds that in Germany the pricing errors of active ETFs are higher than those of passive ETFs. Second, the degree of adverse selection cost in a fund should be positively correlated with the uncertainty of the fund's investment policy (Clarke andand Shastri, 2001). In sum, the extant literature implies that an active ETF can be either more or less liquid than its underlying stock basket, depending on whether the reduction in adverse selection cost outweighs the effect of holding uncertainty.

Hill, Nadig, Hougan, and Fuhr (2015) expect that ETF liquidity and underlying liquidity should be related positively, as the trading costs of underlying stocks form a key cost borne by ETF market makers. Pastor et al. (2020) also predict that a portfolio of small-cap stocks should be less liquid than a portfolio of large-cap stocks. On the other hand, the liquidity of an ETF is one of its key attractions for investors, so ETF creation/redemption activities can feed back into the liquidity of underlying stocks.

The above discussion leads to the following hypothesis:

Hypothesis 1. The difference in liquidity between an active ETF and its underlying portfolio is unclear, but there should be a positive correlation and bidirectional causality between them.

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[4] Specifically, Broman and Shum (2018) find that liquidity of ETFs in core styles is 13% higher than their underlying liquidity. By contrast, they find that the liquidity of ETFs in sector styles is 23% lower than their underlying liquidity.

2.2.2. Effect of diversification on ETF liquidity

Diversification can affect a portfolio's bid-ask spread through its impact on the portfolio's adverse selection cost. Kyle (1985) and Glosten and Milgrom (1985) contend that the presence of traders who have superior information about the fundamental value of a stock can impose adverse selection costs on liquidity traders and market makers. In turn, market makers widen the bid-ask spread and thus recoup the costs (such as the transaction costs of illiquid components and the personnel costs of following up investees) from liquidity traders. Van Ness et al. (2001) find that adverse selection costs correlate positively with a stock's volatility or its idiosyncratic risk. As idiosyncratic risk can be largely diversified away in a stock portfolio, theoretical models of stock basket trading predict that the adverse selection cost of a stock basket will be less than the weighted sum of the adverse selection costs of its stock components (Gorton and Pennacchi, 1993; Subrahmanyam, 1991). Accordingly, ETF diversification should increase ETF liquidity.

However, other studies offer at least two explanations why diversification can decrease ETF liquidity. First, Hamm (2014) suggests that there is a feedback loop between the portfolio's liquidity and the liquidity of its underlying securities. Stocks become less liquid as they are incorporated into ETFs, and more diversified portfolios encourage more uninformed traders to migrate from underlying stocks to ETFs. As a result, Hamm (2014) predicts that all else being equal, a more diversified portfolio ends up holding less liquid stocks. Second, Pastor et al. (2020) theorize and find that diversification and liquidity of constituent stocks in a portfolio are substitutes; specifically, funds with more diversified portfolios tend to hold less liquid stocks.

Given these opposite effects, we formulate the following hypothesis:

Hypothesis 2. The effect of diversification on active ETF liquidity is unclear.

2.2.3. Explaining the gap between ETF liquidity and underlying liquidity

Research on the determinants of stock liquidity is very well established (e.g., Benston and Hagerman, 1974; Branch and Freed, 1977; Demsetz, 1968; Hamilton, 1978; Laux, 1993; Stoll, 1978, 2000; Tinic, 1972; Tinic and West, 1972). Most studies find that trading characteristics including dollar trading volume, return volatility, market capitalization, and stock price explain the cross-sectional variation in bid-ask spreads. When an ETF is traded on an exchange, it has its own trading characteristics. Thus, it is reasonable to predict that differences in trading characteristics could determine the gap between an ETF's liquidity and the liquidity of its underlying stock portfolio.

Some ETF-specific characteristics may also affect this gap. First, an ETF's premium or discount, i.e., pricing error, signal noise trader risk (DeLong, Shleifer, Summers, and Waldmann, 1990) or inefficiency in its creation/redemption mechanism and operation (Rompotis, 2012). According to DeLong et al. (1990), noise trader risk increases the inventory risk faced by market makers, so a stock or portfolio with more noise trader risk or more pricing error is expected to have a wider bid-ask spread. Moreover, Rompotis (2012) argues that pricing error signals inefficiency in the ETF pricing system, and ETFs with large pricing errors will attract fewer traders, lowering their liquidity in the secondary market. Consequently, we forecast that the larger is the pricing error, the wider is the gap between ETF and underlying liquidity. ETF age (number of months since inception) may also affect the liquidity gap. In its early life, an ETF may suffer low liquidity because of inadequate marketing or insufficient tracking, which could improve when it becomes more established. Accordingly, we propose that

Hypothesis 3. The liquidity gap between an active ETF and its underlying portfolio can be attributed to discrepancies in their trading characteristics and to the ETF's pricing error and age.

2.3. Data

We examine the U.S. market, for comparability with previous studies and because in the United States active ETFs, like passive ones, are required to release their holdings daily. We start with a list of ETFs active in the United States as of January 2018 from Morningstar: 204 ETFs with a total AUM of USD 43.4 billion (see Table 2.1). This number is reduced to 67 ETFs with a total AUM of USD 6.46 billion when we select only equity ETFs. We further exclude 36 ETFs founded after 2015 to ensure at least two years of daily data for each of our ETFs. From the remaining 31 ETFs, we drop one ETF that has an AUM below our threshold of at least USD 5 million, and seven ETFs that do not have daily data on their holdings, as they hold large positions in special investments like Bitcoins. Our final sample comprises 23 U.S. active equity ETFs with total AUM of USD 3.28 billion, representing 50.74% of AUM of all U.S. active equity ETFs as of January 2018. The details of these ETFs can be found in Appendix A.1.

Table 2.1. Descriptive Statistics of U.S. Active ETF Market as of January 2018
Notes: Statistics are computed from the Morningstar database. ETFs are grouped by sector according to the Morningstar classification.

Category	AUM in USD	% Pct in AUM	Number of ETFs	% Pct in Number
Allocation	1,578,677,212	3.64%	21	10.29%
Alternative	1,670,715,625	3.85%	33	16.18%
Commodities	1,106,078,014	2.55%	7	3.43%
Convertibles	58,347,831	0.13%	1	0.49%

Equity	6,464,163,168	14.90%	67	32.84%
Fixed Income	31,778,049,941	73.22%	62	30.39%
Tax Preferred	741,845,120	1.71%	13	6.37%
Total	43,397,876,911	100.00%	204	100.00%

To be consistent with other empirical studies of mutual or closed-end funds (Clarke and Shastri, 2001; Manzler, 2004; Neal and Wheatley, 1998), we intended to gather our ETF data one year after inception date. However, this would have reduced our sample size, as many ETFs in our final list were founded in the second half of 2015. Therefore, we decided to collect each ETF's data from six months after its inception date up to the end of 2017. All 23 sample ETFs were still operating as we wrote this paper. We retrieve their holdings data (components and their weights) and net asset value (NAV) from Morningstar. Over the study period, from January 2011 to December 2017, the 23 ETFs in our sample held 2,231 different stocks, of which 93 were non-U.S. stocks. Daily trading data and stock characteristics are taken from the CRSP database for U.S. stocks and from Bloomberg for non-U.S. stocks.

We use two popular liquidity proxies: the closing bid-ask spread and the Amihud (2002) illiquidity. The daily closing bid-ask spread is calculated as 100%*(*Ask–Bid*)/*Mid*, where *Ask* (*Bid*) is the closing ask (bid) price in CRSP and *Mid* is the average of *Ask* and *Bid* (see Chung and Zhang, 2014). The Amihud illiquidity on a given day is defined as that day's absolute return divided by the dollar trading volume for that day; that is, *|Return|/(ClosingPrice*TradingVolume)*. This measure of liquidity gives the absolute percentage price change per dollar of trading volume, or the price impact of order flow for that day. The larger the Amihud measure, the more illiquid the security. In our analysis, we scale the Amihud illiquidity by 10^6, making it the price impact of a million-dollar volume.

Given the holdings data of each ETF over time, we construct the underlying portfolio bid-ask spread as the average of the components' bid-ask spreads, weighted by the stock's percentage of the portfolio value. We compute the weighted average Amihud illiquidity of the underlying portfolio in the same way. Following Manzler (2004), we assume that short-term holdings and cash have zero spreads. Finally, there are 18,903 fund-day observations in our data set.

2.4. Empirical results

Section 2.4.1 compares the liquidity of ETFs with that of their underlying components. Section 2.4.2 measures and explains the effect of diversification on active ETF liquidity. In Section 2.4.3, we attempt to explain the liquidity difference by discrepancies in various trading characteristics and ETF-specific characteristics.

2.4.1. Is the whole less than the sum of its parts?

To assess the magnitude of the difference between an active ETF's liquidity and its underlying portfolio liquidity, we compare their closing bid-ask spread and Amihud illiquidity. Table 2.2 Panel A shows summary statistics for the means of the ETF liquidity and underlying liquidity. For all 23 active ETFs in our sample, in Panel A we find surprising evidence that their average closing bid-ask spread is significantly higher than that of their underlying stock baskets. Using Amihud illiquidity does not greatly change our results: for 19 ETFs the average Amihud illiquidity is higher than that of the corresponding underlying portfolios, whereas for the other four we get an opposite but statistically weaker result. Our results for active ETFs contrast with the empirical findings for passive ETFs by Hedge and McDermott (2004), Marshall et al. (2018), and Broman and Shum (2018). Our findings suggest that for active ETFs, the effect of holding uncertainty dominates the effect of diversification on adverse selection costs, making active ETF liquidity lower than underlying liquidity.

In Table 2.2, Panel B, we group our active ETFs into different sectors according to Morningstar's ETF sector classifications and average their liquidities within each sector. In accord with our findings in Panel A, we observe that both the average bid-ask spread and the average

Table 2.2. Liquidity Difference between ETFs and Underlying Portfolios

Notes: Table 2.2 Panel A reports the averages of bid-ask spreads and Amihud illiquidity of each ETF and its corresponding underlying portfolio between 2011 and 2017. Bid-ask spreads and Amihud illiquidity are calculated using the following formulas:

Bid-Ask Spread (in percentage) = 100%(Ask Price – Bid Price)/Mid*

Amihud Illiquidity = 10^6 **|Return|/(ClosingPrice*TradingVolume)*

For an underlying portfolio, its bid-ask spread or Amihud illiquidity is the weighted average of the bid-ask spreads or Amihud illiquidities of its components, with the weight being the percentage of stock value in the portfolio. In Panel B, ETFs are grouped into sectors according to the sector classification of Morningstar. Liquidity figures for each sector are the arithmetic average of liquidity measures of all ETFs in this sector over the research period. This table also shows the *t*-statistics and the significance of the mean difference test between liquidity measures of an ETF and its underlying portfolio. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. By individual ETF

	Bid-Ask Spread				Amihud Illiquidity			
ETF	ETF Average	Underlying Average	Difference	*t*-Statistic	ETF Average	Underlying Average	Difference	*t*-Statistic
	(1)	(2)	(3)=(1)-(2)		(4)	(5)	(6)=(4)-(5)	
AADR	0.924	0.199	0.726	13.09***	48.27	0.001	48.27	11.41***
EMLP	0.108	0.073	0.036	3.42***	0.001	0.0002	0.001	11.51***
FFTY	0.141	0.037	0.105	24.71***	0.024	0.0001	0.024	18.27***
FWDD	0.883	0.032	0.851	13.23***	53.24	0.0001	53.24	14.39***
HECO	0.609	0.030	0.579	8.94***	69.57	0.00003	69.56	13.13***
HUSE	0.391	0.025	0.366	17.35***	41.24	0.000001	41.23	11.96***
PSR	0.187	0.029	0.158	33.41***	6.30	0.0001	6.301	7.42***
SMCP	0.375	0.093	0.282	14.50***	88.04	0.001	88.04	8.00***
SYE	0.366	0.021	0.346	52.91***	35.06	0.00001	35.07	12.8***
SYG	0.402	0.021	0.381	24.05***	12.69	0.00002	12.69	7.98***
SYLD	0.110	0.056	0.055	25.39***	0.016	0.0001	0.016	5.27***
SYV	0.438	0.033	0.405	12.53***	52.91	0.00003	52.92	14.91***
TTFS	0.288	0.033	0.255	16.52***	20.58	0.00006	20.58	5.83***
UTES	0.178	0.025	0.153	47.84***	31.36	0.00003	31.36	5.32***
VALX	0.332	0.066	0.256	6.45***	3.23	0.0004	3.23	3.87***
WBIA	0.138	0.038	0.100	51.99***	0.037	0.00006	0.037	17.18***
WBIB	0.141	0.041	0.099	51.51***	0.032	0.00004	0.032	21.68***
WBIC	0.150	0.037	0.113	58.42***	0.022	0.00002	0.022	20.22***
WBID	0.153	0.038	0.115	56.60***	0.031	0.00005	0.031	20.66***
WBIE	0.142	0.026	0.116	62.82***	0.027	0.00002	0.027	-2.73***

WBIF	0.147	0.025	0.123	62.61***	0.023	0.00001	0.023	-1.81*
WBIG	0.156	0.024	0.132	70.76***	0.018	0.00001	0.018	-2.8**
WBIL	0.148	0.026	0.123	62.05***	0.025	0.00002	0.025	-1.68*

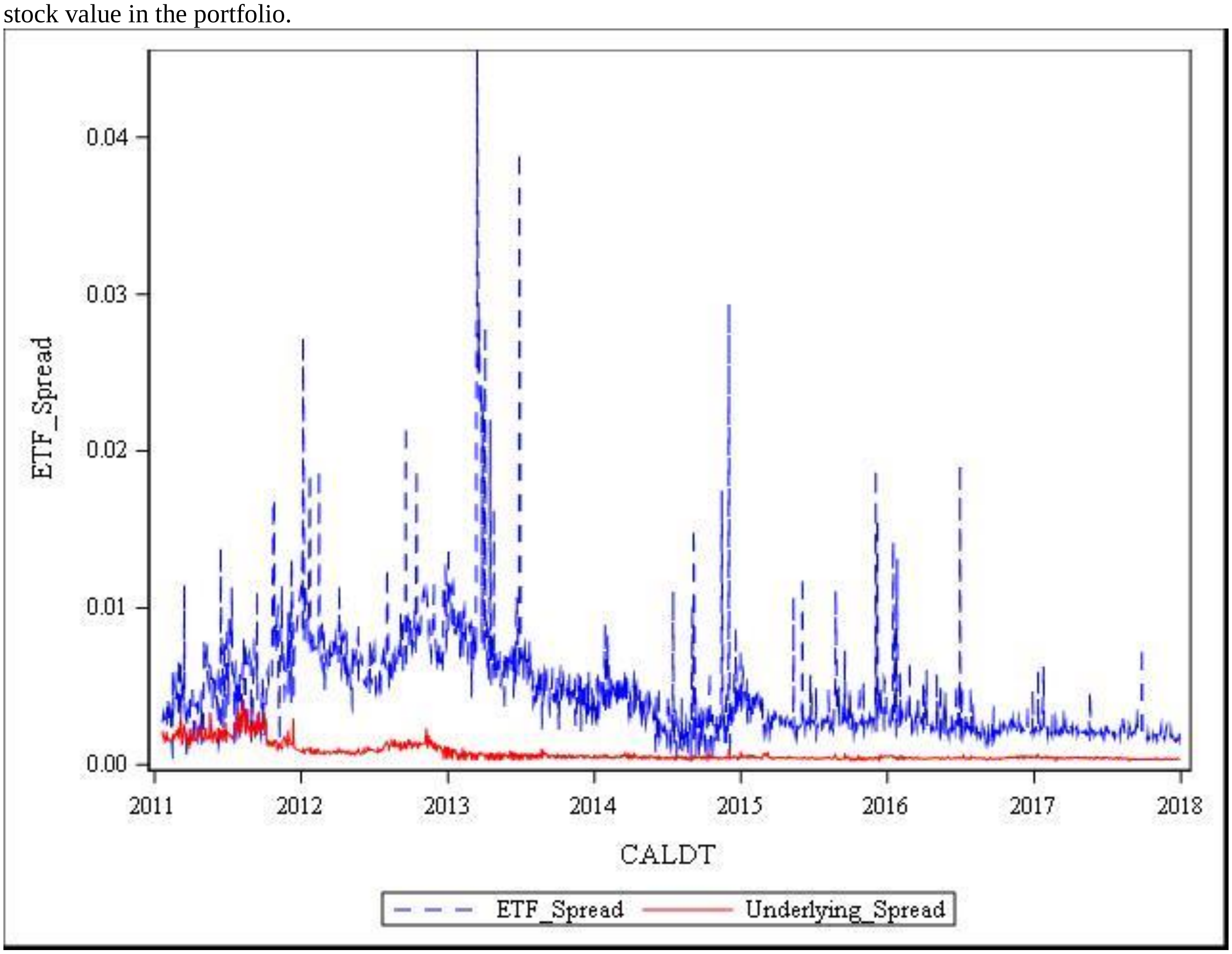
Panel B: By Investment Category

Category	Bid-Ask spread				Amihud Illiquidity			
	ETF Average	Underlying Average	Difference	*t*-Statistic	ETF Average	Underlying Average	Difference	*t*-Statistic
	(1)	(2)	(3)=(1)-(2)		(4)	(5)	(6)=(4)-(5)	
Energy Sector Equity	0.11	0.07	0.04	3.42***	0.13	0.08	0.05	11.51***
Global Equity Large Cap	0.91	0.21	0.70	13.09***	48.27	0.359	47.91	11.41***
Other Sector Equity	0.6	0.03	0.57	8.94***	69.57	0.118	69.45	13.13***
Real Estate Sector Equity	0.2	0.03	0.17	33.41***	6.30	0.0002	6.30	7.42***
US Equity Large Cap Blend	0.4	0.03	0.37	20.29***	25.58	0.107	25.47	18.05***
US Equity Large Cap Growth	0.3	0.02	0.28	28.29***	6.53	0.039	6.49	7.79***
US Equity Large Cap Value	0.4	0.03	0.37	22.75***	43.99	0.096	43.90	19.55***
US Equity Mid Cap	0.2	0.04	0.16	26.61***	4.06	1.20	2.85	4.16***
US Equity Small Cap	0.4	0.1	0.3	14.50***	88.04	0.004	88.03	8.00***
Utilities Sector Equity	0.1	0.02	0.08	47.84***	31.36	0.0002	31.36	5.32***

Amihud illiquidity for each sector ETF are significantly higher than those of the corresponding underlying portfolios.

In order to visualize the bid-ask spread difference between ETFs and their underlying portfolios over time, we plot the daily means of all ETFs' bid-ask spreads and underlying bid-ask spreads in Figure 2.1. While the underlying portfolio spread is quite stable over time, the active ETF spread is much more volatile. The standard deviation of the mean spread over the period is 1% for ETFs, compared to a marginal 0.05% for their underlying portfolios.

Figure 2.1. Average Bid-ask Spreads of ETFs and their Underlying Portfolios Over Time
Notes: An ETF's bid-ask spreads are its daily closing bid-ask spreads. Bid-ask spreads of its underlying portfolio are measured as the weighted average bid-ask spreads of the component stocks, with the weight being the percentage of stock value in the portfolio.



To quantify the relationship between active ETF and underlying liquidity, we compute the Pearson correlation between ETF liquidity measures and underlying liquidity measures. Then we use Fisher transformation to test the significance of these relationships. Table 2.3 presents our empirical results. Out of 23 ETFs in the sample, 15 exhibit statistically significant correlations in liquidity with their underlying portfolios. However, these correlations are not all in the same direction, with nine being positive and 6 being negative. While there are fewer significant correlations in the Amihud illiquidity results, these ten correlations are all positive. Across the two liquidity proxies, the significant relationship in liquidity is positive and consistent for five ETFs (EMLP, FFTY, PSR, SYE, and SYG), and opposite for another five (UTES, WBIA, WBIB, WBIC, and WBID). Nine ETFs show no significant correlations using either the bid-ask spread or the Amihud illiquidity measure. Overall, our evidence from static correlation tests is quite mixed.

Table 2.3. Static Correlations between ETF Liquidity and Underlying Liquidity

Notes: This table presents the Pearson correlation (*Corr*) of ETF liquidity and underlying liquidity measured by the bid-ask spread and Amihud illiquidity (see Table 2.2 for more details). It also shows the results of a correlation test using Fisher's transformation (*ZVal*). ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

		Bid-Ask Spread		Amihud Illiquidity	
ETF	Number of Observations	Corr	ZVal	Corr	ZVal
AADR	1426	0.13***	0.13	-0.02	-0.02
EMLP	996	0.61***	0.70	0.36***	0.38
FFTY	540	0.16***	0.16	0.33***	0.35
FWDD	1247	0.03	0.03	-0.03	-0.03
HECO	1199	0.03	0.02	-0.04	-0.04
HUSE	1177	0.09**	0.10	0.04	0.04
PSR	1071	0.28***	0.29	0.07**	0.07
SMCP	530	0.03	0.03	0.15	0.15
SYE	729	0.33***	0.35	0.25***	0.26
SYG	730	0.19***	0.19	0.15***	0.15
SYLD	917	-0.01	-0.01	-0.02	-0.02
SYV	729	0.05	0.05	-0.01	-0.01
TTFS	1062	0.53***	0.59	-0.01	-0.01
UTES	366	-0.22***	-0.23	0.24***	0.25
VALX	659	0.05	0.05	-0.01	-0.01
WBIA	690	-0.24***	-0.25	0.41***	0.43
WBIB	690	-0.22***	-0.22	0.24***	0.25
WBIC	691	-0.12**	-0.12	0.35***	0.37
WBID	691	-0.22***	-0.23	0.21***	0.22
WBIE	692	-0.05	-0.05	-0.04	-0.04
WBIF	691	-0.07*	-0.07	-0.005	-0.01
WBIG	690	-0.05	-0.05	0.029	0.03
WBIL	690	0.01	0.01	-0.014	-0.01
Overall	18,903	0.14***	0.15	-0.01	-0.01

To examine dynamic interactions, we use a vector autoregressive model (VAR) to quantify the lead-lag relationship. Specifically, we estimate the two following equations of the VAR model for each ETF:

$$ETF\_LIQ_t = \alpha_0 + \sum_{j=1}^{k} \beta_j \, ETF\_LIQ_{t-j} + \sum_{j=1}^{k} \gamma_j \, Underlying\_LIQ_{t-j} + \varepsilon_t \qquad (1)$$

and

$$Underlying\_LIQ_t = \eta_0 + \sum_{j=1}^{k} \mu_j \, Underlying\_LIQ_{t-j} + \sum_{j=1}^{k} \lambda_j \, ETF\_LIQ_{t-j} + \phi_t, \qquad (2)$$

where ETF_LIQ_t and $Underlying\_LIQ_t$ are the ETF and underlying liquidity, respectively. The liquidity proxy is either the closing bid-ask spread or the Amihud illiquidity ratio. Following Chordia, Sarkar, and Subrahmanyam (2005), we choose the number of lags, k, in Eqs. (1) and (2) on the basis of the Akaike information criterion or the Schwarz Bayesian criterion. If these two criteria imply different lag lengths, we choose the lesser lag length for the sake of parsimony.

Table 2.4 presents pairwise Granger causality tests between ETF and underlying liquidity in Eqs. (1) and (2) for each ETF. For each ETF and each proxy of liquidity, there are two tests. The null hypothesis of Test 1 is that the ETF liquidity is influenced by itself but not by the underlying liquidity; that is, all γ_j in Eq. (1) are jointly equal to zero. The null hypothesis of Test 2 is that the underlying liquidity is influenced by itself but not by the ETF liquidity; that is, all λ_j in Eq. (2) are jointly equal to zero.

Table 2.4. Granger Causality Wald Test between ETF and Underlying Liquidity

Notes: This table presents the results of a Granger causality test between ETF and underlying liquidity in the VAR(k) models of Eq. (1) and Eq. (2) using the optimal number of lags (k) as the lowest suggested by the Akaike information criterion and the Schwarz Bayesian criterion.

$$ETF\_LIQ_t = \alpha_0 + \sum_{j=1}^{k} \beta_j\, ETF\_LIQ_{t-j} + \sum_{j=1}^{k} \gamma_j\, Underlying\_LIQ_{t-j} + \varepsilon_t \quad (1)$$

$$Underlying\_LIQ_t = \eta_0 + \sum_{j=1}^{k} \mu_j\, Underlying\_LIQ_{t-j} + \sum_{j=1}^{k} \lambda_j\, ETF\_LIQ_{t-j} + \phi_t, \quad (2)$$

where ETF_LIQ_t and $Underlying\_LIQ_t$ are ETF and underlying liquidity, respectively. Liquidity is measured by either the bid-ask spread or the Amihud illiquidity ratio (see Table 2.2 for more details). Test 1 has the null hypothesis that ETF liquidity is affected by itself but not by the underlying liquidity. Test 2 has the null hypothesis that underlying liquidity is affected by itself but not by the ETF liquidity. The numbers in each column are the Chi-square statistics of a Granger causality test. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Bid-Ask Spread		Amihud Illiquidity	
ETF	Test 1	Test 2	Test 1	Test 2
AADR	0.01	5.72**	0.57	0.48
EMLP	0.47	28.13***	0.63	10.96***
FFTY	6.77***	10.39***	0.07	0.06
FWDD	0.89	0.79	0.12	0.68
HECO	2.09	2.78*	0.00	2.51
HUSE	8.67	4.48**	0.05	19.81***
PSR	36.68***	6.52**	0.07	0.1
SMCP	0.27	0.99	2.20	0.29
SYE	19.51***	43.93***	2.7	1.84
SYG	5.27**	8.88***	0.25	0.01
SYLD	0.97	8.38**	0.02	0.3
SYV	1.52	0.07	0.22	1.12
TTFS	172.51***	6.26**	1.83	2.33
UTES	13.8***	2.43	3.62*	0.04
VALX	0.53	0.48	2.55	4.38
WBIA	18.18***	6.67***	5.47*	3.96*
WBIB	16.69***	3.30**	1.48	3.67*
WBIC	7.66***	1.52	15.15***	0.41
WBID	12.72***	3.7	0.87	16.24***
WBIE	0.88	0.89	0.21	0.5
WBIF	5.99	5.35	0.53	0.24
WBIG	7.85**	0.42	0.85	1.17
WBIL	5.57*	4.03	0.01	0.03

The Granger test results in Table 2.4 show weak evidence of Granger causation between the ETF liquidity and the underlying stock basket liquidity. The results of Test 1 show that 12 out of 23 ETF spreads are dependent on themselves and their lagged underlying spreads. Similarly, the results of Test 2 indicate that 12 out of 23 underlying portfolio spreads are affected by themselves and their lagged ETF spreads. Only seven ETFs exhibit a bi-directional Granger causality when the bid-ask spread is used as the liquidity measure. And when we use Amihud illiquidity as the liquidity proxy, only one ETF has a significant Chi-square statistic in both Test 1 and Test 2.

The VAR and Granger tests do not account for the possibility that ETF liquidity and underlying liquidity can affect each other contemporaneously. To take into account both the lead-lag and the contemporary relationship, we estimate the following equations, following Hong, Lin, and Wu (2012):

$$ETF\_LIQ_t = \alpha_0 + \sum_{j=1}^{k} \beta_j \, ETF_{LIQ_{t-j}} + \sum_{j=0}^{k} \gamma_j \, Underlying_{LIQ_{t-j}} + \varepsilon_t \tag{3}$$

$$Underlying\_LIQ_t = \eta_0 + \sum_{j=1}^{k} \mu_j \, Underlying_{LIQ_{t-j}} + \sum_{j=0}^{k} \lambda_j \, ETF_{LIQ_{t-j}} + \phi_t \, , \tag{4}$$

where ETF_LIQ_t and $Underlying\_LIQ_t$ are the ETF and underlying liquidity, respectively. The liquidity proxy is either the closing bid-ask spread or the Amihud illiquidity ratio. The number of lags, k, in Eqs. (3) and (4) is the same as in Eqs. (1) and (2). The benefits of Eqs. (3) and (4) are that they allow us to test their parameter values and to infer the sign of the correlation between ETF and underlying liquidity. Specifically, we perform two tests. In Test 3 for Eq. (3), we test whether γ_j = 0 for all j. This test will indicate whether ETF liquidity is affected by contemporary and lagged underlying liquidity. In Test 4 for Eq. (3), we test whether the sum of response coefficients, $\sum_{j=0}^{k} \gamma_j$, is different from zero. This test allows us to infer the sign of the correlation between ETF and underlying liquidity. Similarly, in Test 3 for Eq. (4), we test whether λ_j = 0 for all j. In Test 4 for Eq. (4), we test whether the sum of coefficients, $\sum_{j=0}^{k} \lambda_j$, is different from zero.

The F-statistics of Tests 3 and 4 are shown in Table 2.5, as are the sums of coefficients for Test 4, $\sum_{j=0}^{k} \gamma_j$ and $\sum_{j=0}^{k} \lambda_j$. In Panel A, we use quoted bid-ask spread as the liquidity measure. Using Test 1, we find some evidence of contemporary and lagged effects of underlying spread on ETF spread and vice versa. The results of Test 3 for Eq. (3) show that 12 out of 23 ETF spreads are affected by both contemporary and lagged values of their underlying spreads. Similarly, the results of Test 3 for Eq. (4) indicate that 10 out of 23 underlying spreads are dependent on both contemporary and lagged values of their ETF spreads. In Test 4, our results support a positive correlation between ETF spread and underlying spread. The sum of coefficients $\sum_{j=0}^{k}$ in Test 4 for Eq. (3) is significantly positive for 9 ETFs and significantly negative for 6, whereas in Test 4 for Eq. (4), the sum of coefficients $\sum_{j=0}^{k} \lambda_j$ is significantly positive for 8 ETFs and significantly negative for 3. The average sum of coefficients $\sum_{j=0}^{k} \gamma_j$ is 4.27, much greater than the average sum of coefficients $\sum_{j=0}^{k} \lambda_j$, which is -0.03. These figures indicate that underlying liquidity has greater impact on ETF liquidity than vice versa.

In Panel B, we use the Amihud illiquidity ratio to proxy ETF and underlying liquidity. In Test 3 for Eq. (3), we find that 11 out of 23 ETF Amihud illiquidity ratios are affected by both contemporary and lagged values of their underlying Amihud illiquidity ratios. Conversely, 12 out of 23 underlying Amihud illiquidity ratios are dependent on both contemporary and lagged values of their ETF Amihud illiquidity ratios, as appears in the results of Test 3 for Eq. (4). The correlation between ETF and underlying Amihud illiquidity ratios is indicated by Test 4. The sum of coefficients $\sum_{j=0}^{k} \gamma_j$ is significantly positive for 10 ETFs, and the sum of coefficients $\sum_{j=0}^{k} \lambda_j$ is significantly positive for 11 ETFs. None of the ETFs exhibits a significantly negative value for either sum, and the average sum of coefficients $\sum_{j=0}^{k} \gamma_j$ is again substantially higher than the average sum of coefficients $\sum_{j=0}^{k} \lambda_j$. In general, the evidence of contemporary and lagged effects between ETF and underlying liquidity is weak, although the sign of the effect tends to be positive, lending support to Hypothesis 1; and ETF liquidity is affected by underlying liquidity to a greater extent than vice versa.

Table 2.5. Contemporaneous and Lagged Effects of ETF Liquidity and Underlying Liquidity

Notes: This table reports the F-statistics of Test 3 and the F-statistics and the sum of coefficients, $\sum_{j=0}^{k}\gamma_j$ or $\sum_{j=0}^{k}\lambda_j$, of Test 4 when the following equations are regressed using ordinary least squares (OLS):

$$ETF\_LIQ_t = \alpha_0 + \sum_{j=1}^{k}\beta_j\, ETF_{LIQ_{t-j}} + \sum_{j=0}^{k}\gamma_j\, Underlying_{LIQ_{t-j}} + \varepsilon_t \quad (3)$$

$$Underlying\_LIQ_t = \eta_0 + \sum_{j=1}^{k}\mu_j\, Underlying_{LIQ_{t-j}} + \sum_{j=0}^{k}\lambda_j\, ETF_{LIQ_{t-j}} + \phi_t\ , \quad (4)$$

where ETF_LIQ_t and $Underlying\_LIQ_t$ are the ETF and underlying liquidity, respectively. The liquidity proxy is either the closing bid-ask spread (in Panel A) or the Amihud illiquidity ratio (in Panel B). The number of lags k in Eqs. (3) and (4), is the same as the number of lags k in Eqs. (1) and (2) in Table 4. In Test 3 for Eq. (3), we test whether $\gamma_j = 0$ for all j. In Test 4 for Eq. (3), we test whether the sum of coefficients, $\sum_{j=0}^{k}\gamma_j$, is significantly different from zero. Similarly, in Test 3 for Eq. (4), we test whether $\lambda_j = 0$ for all j. In Test 4 for Eq. (4), we test whether the sum of coefficients, $\sum_{j=0}^{k}\lambda_j$, is different from zero. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Using Bid-Ask Spread as Liquidity Measure

ETF	Effect of Underlying Liquidity Eq. (3)			Effect of ETF Liquidity Eq. (4)		
	Test 3	Test 4		Test 3	Test 4	
	F-statistics	$\sum_{j=0}^{k}\gamma_j$	F-statistics	F-statistics	$\sum_{j=0}^{k}\lambda_j$	F-statistics
AADR	18.3***	2.37	7.37***	21.23***	0.03	5.97**
EMLP	336.85***	8.25	140.43***	360***	0.02	103.21***
FFTY	4.88***	2.29	9.59***	6.70***	0.01	12.81***
FWDD	0.31	6.09	0.67	0.29	0.0001	0.34
HECO	1.06	10.53	1.44	1.41	0.0001	1.32
HUSE	4.91***	9.51	9.77***	2.82*	0.0005	5.17**
PSR	28.28***	8.84	53.88***	12.94***	0.003	22.04***
SMCP	1.25	0.09	0.09	1.61	0.0004	0.09
SYE	22.68***	15.01	41.85***	35.30***	0.006	70.57***
SYG	7.04***	15.04	12.10***	8.87***	0.002	17.28***
SYLD	0.32	0.01	2.09*	2.78**	0.0004	0.09
SYV	1.00	2.04	1.91	0.27	0.0005	0.44
TTFS	73.00***	18.78	196.62***	15.53***	0.002	10.21***
UTES	7.59***	-1.73	14.87***	1.90	-0.011	3.79*
VALX	0.79	3.32	1.01	0.76	0.0001	0.05
WBIA	0.06	-0.66	1.23	19.52***	-0.015	4.12**
WBIB	8.65***	-0.37	17.23***	1.96	-0.12	3.75*
WBIC	3.84**	-0.01	7.35***	0.77	-0.29	1.15
WBID	3.18**	-0.01	9.03***	0.92	-0.36	1.26
WBIE	0.12	-0.16	0.48	0.65	-0.01	0.84
WBIF	1.26	-0.77	0.32	1.13	-0.002	0.02
WBIG	1.03	-0.12	3.63**	0.81	-0.0026	0.18
WBIL	0.18	-0.01	2.94*	0.22	0.003	2.17
Average		4.27			-0.03	

Panel B. Using Amihud Illiquidity Ratio as Liquidity Measure

ETF	Effect of Underlying Liquidity Eq. (3)			Effect of ETF Liquidity Eq. (4)		
	Test 3	Test 4		Test 3	Test 4	
	F-statistics	$\sum_{j=0}^{k}\gamma_j$	F-statistics	F-statistics	$\sum_{j=0}^{k}\lambda_j$	F-statistics

AADR	0.43	-1.32	0.44	0.39	-0.0008	0.89
EMLP	82.62***	0.85	37.45***	88.64***	0.043	22.93***
FFTY	32.62***	57.56	22.50***	32.62***	0.001	26.05***
FWDD	0.66	-16.22	0.60	0.71	-0.0001	0.63
HECO	0.75	-13.23	0.57	2.01	-0.0001	4.01
HUSE	0.53	36.12	0.73	10.41***	0.0001	15.81***
PSR	2.55*	12.68	1.53	2.56*	0.002	3.19*
SMCP	4.65***	14.94	6.31**	3.69**	0.002	4.39**
SYE	25.19***	10.43	27.45***	24.74***	0.006	13.06***
SYG	8.31***	25.10	7.56***	8.18***	0.001	7.23***
SYLD	0.31	-23.56	0.17	0.51	-0.0001	0.04
SYV	0.15	1.12	0.04	0.59	0.002	0.33
TTFS	0.77	1.12	0.09	0.93	0.0002	1.03
UTES	11.51***	26.9	16.42***	9.63***	0.05	10.61***
VALX	0.31	0.003	0.27	0.03	0.0001	0.06
WBIA	7.72***	45.63	13.54***	54.15***	0.002	33.58***
WBIB	23.29***	11.02	19.66***	24.45***	0.0025	9.12***
WBIC	42.78***	16.65	58.5***	34.68***	0.004	21.59***
WBID	15.43***	7.11	3.76*	16.61***	0.001	1.44
WBIE	0.57	-0.004	0.98	0.71	-0.76	1.36
WBIF	0.73	-0.001	0.01	0.13	-3.2	0.43
WBIG	0.11	0.0001	0.001	0.82	0.61	0.18
WBIL	0.08	-0.001	0.21	0.07	-1.194	0.20
Average		9.26			-0.19	

2.4.2. Determinants of ETF liquidity and the effect of diversification

To study the effect of ETF diversification on ETF liquidity, we estimate the following equation:

$$ETF\_LIQ_{E,t} = a_0 + a_1 LnV_{E,t} + a_2 \sigma_{E,t}^{\,2} + a_3 LnMV_{E,t} + a_4 LnP_{E,t} + a_5 PRE_{E,t} + a_6 DI_{i,E,t} + e_{E,t}\,, \qquad (5)$$

where $ETF\_LIQ_{E,t}$ is either an ETF's daily closing bid-ask spread or its Amihud illiquidity. ETF characteristics include the natural logarithm of daily dollar volume, $LnV_{E,t}$; return variance, $\sigma_{E,t}^{2}$, using a 5-day rolling window; the natural logarithm of market capitalization, $LnMV_{E,t}$, calculated as net asset value multiplied by number of shares outstanding; the natural logarithm of end-of-day market price, $LnP_{E,t}$; the pricing error, $PRE_{E,t}$, measured as the absolute daily deviation of an ETF's price from its NAV; and the degree of ETF diversification, $DI_{i,E,t}$.

Although diversification is an important concept in finance, there is not yet an accepted standard for measuring it. In fact, there are many proxies for a concentration index—the inverse of the diversification index—and there is no profound reason for using any particular one, other than that it is mathematically different and may empirically work better than other forms (Woerheide and Persson, 1992).

In Eq. (5) we use two different measures of ETF diversification, both based on the Herfindahl-Hirschman index. Our Diversification Index 1, $DI_{1,E,t}$, is computed by subtracting a portfolio's Herfindahl Index from 1 as follows:

$$DI_{1,E,t} = 1 - HI_1 = 1 - \sum_{i=1}^{N} W_i^2\,, \qquad (6)$$

where $DI_{1,E,t}$ is the Diversification Index 1; HI_1 is the Herfindahl Index of an ETF's underlying stock portfolio; W_i is the value-based weight of stock i in decimal form in the portfolio; and N is the number of securities in the portfolio.

As an underlying portfolio can be concentrated in a few industry sectors, we complement this measure with Diversification Index 2, calculated from Eq. (7):

$$DI_{2,E,t} = 1 - HI_2 = 1 - \sum_{j=1}^{M} V_j^2 , \tag{7}$$

where $DI_{2,E,t}$ is Diversification Index 2; HI_2 is the Herfindahl Index of an ETF's industry-based portfolio; V_j is the value-based weight of industry j in decimal form in the underlying portfolio; and M is the number of industries in the portfolio. For U.S. stocks we use the industry classification from the CRSP database, and for non-U.S. stocks, from Bloomberg. Weights of stocks in the same industry code are summed to get the weight of each industry in the ETF's portfolio.

Table 2.6 reports the results of Eq. (5). Panels A and B, for our two diversification proxies, show consistent results. First, regarding the effects of general trading characteristics, the negative and significant coefficient of ETF price, LnP_E, indicates that ETFs with higher prices have relatively higher trading liquidity than those with lower prices, for both liquidity proxies. The impact of dollar trading volume, LnV_E, is also negative, as we expected; however, it is statistically significant only for the Amihud illiquidity. The sign of market value, $LnMV_E$, is negative for the bid-ask spread and positive for the Amihud illiquidity; Stoll (2007) finds a similarly uncertain effect for a sample of U.S. stocks, with opposite effects for stocks on NYSE and on NASDAQ. ETF return variance, σ^2_E, does not seem to influence the liquidity of ETFs. These findings, together with those in section 2.4.1, lead to a noteworthy conclusion: although deriving its value from its underlying portfolio, an ETF has its own liquidity determinants. Our findings help explain why similar ETFs tracking the same index may have different levels of liquidity.

Second, regarding the effects of ETF-specific characteristics, we find that the coefficient of the pricing error, PRE_E, is significantly positive in six out of eight regression specifications in Panel A, suggesting that ETFs with large price deviations from their NAVs experience lower liquidity (i.e., larger bid-ask spreads and higher price impacts) than do those with small pricing errors.

Finally, the diversification coefficients, $DI_{i,E}$, show that a more diversified portfolio of underlying stocks is associated with larger bid-ask spreads and higher price impacts than a less diversified one. These results are contrary to the expectations of Subrahmanyam (1991) and Gorton and Pennacchi (1993) but can be explained by Hamm's (2014) hypothesized negative feedback effect and Pastor et al.'s (2020) hypothesized trade-off between the portfolio's diversification and liquidity.

Table 2.6. Determinants of ETF Liquidity

Notes: Table 2.6 presents the results of model (5) in explaining the variation in ETF liquidity by its trading characteristics and ETF-specific characteristics. Specifically, the estimated model is

$$ETF\_LIQ_t = a_0 + a_1 LnV_{E,t} + a_2 \sigma_{E,t}^{\ 2} + a_3 LnMV_{E,t} + a_4 LnP_{E,t} + a_5 PRE_{E,t} + a_6 DI_{i,E,t} + e_{\ E,t} \ , \quad (5)$$

where $ETF\_LIQ_{E,t}$ is either an ETF's daily closing bid-ask spread or its Amihud illiquidity. $LnV_{E,t}$ is the natural logarithm of ETF daily dollar volume; $\sigma_{E,t}^2$ is ETF return variance using a 5-day rolling window; $LnMV_{E,t}$ is the natural logarithm of daily ETF market value measured as net asset value (NAV) multiplied by number of shares outstanding; and $LnP_{E,t}$ is the natural logarithm of ETF closing trading price. $PRE_{E,t}$ is ETF pricing error measured by the absolute difference between an ETF's NAV and its market price; $DI_{i,E,t}$ is the degree of ETF diversification. DI_i stands for Diversification Index i with i ={1,2}. DI_1 is calculated as $DI_{1,E,t} = 1 - HI_1 = 1 - \sum_{i=1}^{N} W_i^{\ 2}$, where W_i is the weight of stock i in the ETF portfolio; DI_2 is calculated as $DI_{2,E,t} = 1 - HI_2 = 1 - \sum_{j=1}^{M} V_j^{\ 2}$, where V_i is the weight of industry j in the ETF portfolio. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Using Stock-Based Diversification

Independent Variables	Bid-Ask Spread				Amihud Illiquidity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnV_E	-0.001	0.005	-0.001	0.004	-14.89***	-15.12***	-14.87***	-15.06***
	(-0.42)	(1.55)	(-0.38)	(1.28)	(-26.70)	(-26.88)	(-33.24)	(-33.28)
σ^2_E	58.2	44.9	57.16	46.8	6806	6057	6304	5703
	(0.95)	(0.87)	(1.06)	(0.96)	(1.08)	(1.04)	(1.17)	(1.09)
$LnMV_E$	-0.13***	-0.02	-0.11***	-0.021	10.47***	18.31***	13.15***	19.71***
	(-11.37)	(-0.56)	(-13.27)	(-0.57)	(13.62)	(7.30)	(19.01)	(8.80)
LnP_E	-0.12***	-0.10***	-0.06***	-1.08***	-16.10***	-92.5***	-9.68***	-84.9***
	(-3.70)	(-4.11)	(-3.37)	(-4.75)	(-7.02)	(-7.65)	(-7.12)	(-5.00)
PRE_E	0.23***	0.08	0.31***	0.15	66.1***	76.3***	69.9***	78.1***
	(3.68)	(0.47)	(6.37)	(1.05)	(2.63)	(2.77)	(3.07)	(3.17)
$DI_{1,E}$	0.38***	0.14*	0.15***	0.075	26.56***	22.52***	14.91***	21.45***
	(5.02)	(1.84)	(3.58)	(1.26)	(6.91)	(4.72)	(5.02)	(5.26)
ETF fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of Observations	18,903	18,903	18,903	18,903	18,903	18,903	18,903	18,903
Adj.R^2	0.029	0.073	0.05	0.075	0.329	0.349	0.346	0.355

Panel B. Using Industry-Based Diversification

Independent Variables	Bid-Ask Spread				Amihud Illiquidity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LnV_E	-0.002	0.005	-0.001	0.004	-14.91***	-15.12***	-14.88***	-15.06***
	(-0.54)	(1.55)	(-0.47)	(1.29)	(-26.68)	(-26.88)	(-33.27)	(-33.28)
σ^2_E	59.3	45.0	57.5	46.8	6878	6068	6350	5713
	(0.96)	(0.87)	(1.07)	(0.96)	(1.08)	(1.04)	(1.17)	(1.09)
$LnMV_E$	-0.13***	-0.02	-0.02***	-0.017	10.55***	18.58***	13.60***	20.038***
	(-10.39)	(-0.43)	(-11.41)	(-0.44)	(13.07)	(7.17)	(18.92)	(8.60)
LnP_E	-0.072	-1.03***	-0.004	-1.10***	-14.19***	-93.47***	-7.56***	-86.49***
	(-2.31)	(-4.06)	(-0.21)	(-4.70)	(-5.92)	(-7.56)	(-5.22)	(-4.97)
PRE_E	0.23***	0.07	0.29***	0.14	67.14**	75.73**	70.10***	77.64***
	(3.78)	(0.40)	(6.06)	(0.97)	(2.68)	(2.75)	(3.08)	(3.14)
$DI_{2,E}$	0.19***	0.20*	0.26***	0.14*	2.33	24.09***	7.12***	23.93***
	(7.14)	(1.90)	(11.49)	(1.74)	(0.76)	(3.97)	(2.82)	(4.45)

ETF fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of Observations	18,903	18,903	18,903	18,903	18,903	18,903	18,903	18,903
Adj.R^2	0.029	0.073	0.052	0.075	0.328	0.349	0.347	0.355

Pastor et al. (2020, p. 3) argue that "in equilibrium, funds with more-diversified portfolios should be larger and cheaper, they should trade more, and their stock holdings should be less liquid." They use the following model:[5]

$$Ln(Diversification) = b_0 + b_1 LnA + b_2 Lnf + b_3 LnT + b_4 Ln(Stock\ Liquidity) + \varepsilon\ , \tag{8}$$

where *Ln(Diversification)* is the natural logarithm of the fund's degree of diversification; *LnA* is the logarithm of fund size; *Lnf* is the natural logarithm of fund expense ratio; and *LnT* is the natural logarithm of fund turnover. *Ln(Stock Liquidity)* is the natural logarithm of the fund's underlying stock liquidity, measured by comparing the market capitalization of underlying stocks to a benchmark. The authors find that the coefficient b_4 in Eq. (7) is significantly negative, in accord with their prediction that portfolio diversification and underlying stock liquidity are substitutes.

Adapting Eq. (8), we estimate the following model to understand the relationship between diversification and underlying liquidity in the ETF context:

$$Ln(DI_{i,E,t}) = \beta_0 + \beta_1 LnMV_{E,t} + \beta_2 Ln(Underlying\_LIQ_{E,t}) + \varepsilon_{E,t}\ , \tag{9}$$

[5] See Pastor et al. (2020, Equation [26]). They use their theoretically motivated measure of diversification as the primary measure of fund diversification. For robustness checks they also use the Herfindahl index of portfolio weights, the number of stocks in the funds, and the R-squared from a regression of fund returns on benchmark returns.

where $Ln(DI_{i,E,t})$ is the natural logarithm of the degree of ETF diversification; $DI_{i,E,t}$ can be different measures of ETF diversification as defined in Eq. (5); $LnMV_{E,t}$ is the natural logarithm of ETF market capitalization; and $Ln(Underlying\_LIQ_{E,t})$ is the natural logarithm of underlying liquidity. The underlying liquidity of an ETF is measured as the weighted average of the bid-ask spreads or Amihud illiquidity ratios of constituent stocks in that ETF.

Table 2.7 reports the results of Eq. (9) using regressions with pooled, ETF fixed effects, year fixed effects, and both ETF and year fixed effects. Contrary to the proposal of Pastor et al. (2020), we find a negative correlation between the size of an ETF and its degree of diversification, although we do find that its diversification correlates positively with its underlying illiquidity, proxied either by the bid-ask spread or by the Amihud illiquidity ratio. Thus, the empirical results of Eq. (9) not only reaffirm the trade-off between diversification and underlying liquidity but also explain our previous finding of a negative effect of diversification on ETF liquidity.

Table 2.7. Trade-offs between Underlying Liquidity and Degree of ETF Diversification

Notes: Table 2.7 reports the regression results of the following model of the relationship between an ETF's degree of diversification and its underlying liquidity:

$$Ln(DI_{i,E,t}) = \beta_0 + \beta_1 LnMV_{E,t} + \beta_2 Ln(Underlying\_LIQ_{E,t}) + \varepsilon_{E,t}, \quad (9)$$

where $Ln(DI_{i,E,t})$ is the natural logarithm of the degree of ETF diversification; $DI_{i,E,t}$ can be different measures of portfolio diversification from DI_1 to DI_2 (see Table 6 for more details); $LnMV_{E,t}$ is the natural logarithm of ETF market capitalization; and $Ln(Underlying\_LIQ_{E,t})$ is the natural logarithm of underlying liquidity. The underlying liquidity of an ETF is measured as the weighted average of the bid-ask spreads or Amihud illiquidity ratios of its constituent stocks. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Using Bid-Ask Spread as Liquidity Proxy

Independent Variables	$Ln(DI_1)$				$Ln(DI_2)$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$LnMV_E$	-0.015***	-0.004***	-0.017***	-0.016***	-0.034***	0.005	-0.032***	-0.012***
	(-28.56)	(-3.4)	(-31.66)	(-11.17)	(-25.79)	(2.36)	(-24.29)	(-4.88)
$Ln(Underlying\_LIQ_E)$	0.055***	0.122***	0.059***	0.128***	0.075***	0.221***	0.068***	0.228***
	(52.11)	(67.91)	(54.55)	(73.07)	(29.00)	(73.58)	(26.06)	(77.14)
ETF fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of Observations	18,903	18,903	18,903	18,903	18,903	18,903	18,903	18,903
Adj.R^2	0.151	0.377	0.200	0.418	0.070	0.681	0.156	0.699

Panel B. Using Amihud Illiquidity as Liquidity Proxy

Independent Variables	$Ln(DI_1)$				$Ln(DI_2)$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$LnMV_E$	-0.014***	-0.021***	-0.013***	-0.030***	-0.032***	-0.025***	-0.029***	-0.037***
	(-24.25)	(-15.22)	(-24.13)	(-19.11)	(-24.46)	(-10.49)	(-22.96)	(-13.88)
$Ln(Underlying\_LIQ_E)$	0.007***	0.004***	0.007***	0.005***	0.026***	0.012***	0.023***	0.013***
	(21.64)	(9.58)	(21.23)	(13.55)	(35.69)	(17.60)	(29.73)	(19.19)
ETF fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of Observations	18,903	18,903	18,903	18,903	18,903	18,903	18,903	18,903
Adj.R^2	0.053	0.228	0.096	0.261	0.09	0.596	0.165	0.611

2.4.3. Explaining the gap between ETF and underlying liquidity

In this section, we use Stoll's (2000) model as our starting point to study the determinants of the discrepancy between ETF and underlying liquidity:

$$S/P = a_0 + a_1 LnV + a_2\sigma^2 + a_3 LnMV + a_4 LnP + a_5 LnN + e\ , \qquad (10)$$

where *S/P* is stock quoted bid-ask spread; *LnV* is the natural logarithm of stock daily dollar volume; σ^2 is stock return variance; *LnMV* is the natural logarithm of stock market value; *LnP* is the natural logarithm of stock closing price; *LnN* is the natural logarithm of the number of trades per day; and *e* is the error term.

According to Stoll (2000), the rationale for the independent variables in Eq. (10) is based primarily on order processing and inventory considerations that are also relevant for ETFs. Compared to stocks or closed-end funds, ETFs are more transparent in operation and are expected to have lower adverse selection costs. Specifically, increases in volume, the number of trades, and firm size increase the likelihood of finding a trading counterparty, hence reducing the risk of taking inventory. The stock's return variance indicates the risk of adverse price change of a stock held in inventory. Finally, price controls for risk, in that low-price stocks tend to be riskier.

Adapting Stoll's (2000) model, to explain the liquidity gap we use the differences between an ETF and its underlying portfolio in four trading characteristics: dollar trading volume, market capitalization, stock return variance, and closing price. Adding two more independent variables to account for the effect of pricing error and ETF age yields the following equation:

$$Liquidity\_Difference_t = \beta_0 + \beta_1 Df\_LnV_t + \beta_2 Df\_\sigma_t^2 + \beta_3 Df\_LnMV_t + \beta_4 Df\_LnP_t + \beta_5 PRE_t + \beta_6 OLD_t + \varepsilon_t , \quad (11)$$

where $Liquidity\_Difference_t$ is the difference in daily liquidity between an ETF and its underlying stock portfolio using either the closing bid-ask spread or the Amihud illiquidity ratio as a liquidity proxy. Recall that the liquidity of an underlying portfolio is measured as the weighted average liquidity of the underlying stocks with the weight being the percentage of stock value in the ETF portfolio. Df_LnV_t, $Df\_\sigma_t^2$, Df_LnMV_t, and Df_LnP_t are daily differences in the logarithm of dollar trading volume, return variance, the logarithm of market capitalization, and the logarithm of price between an ETF and its underlying portfolio, respectively. We use a 5-day rolling window to compute return variances. We calculate the trading characteristics of an underlying portfolio similarly, using the weighted average of its components with the weight based on the percentage of stock value in the portfolio. For instance, the dollar trading volume of the underlying portfolio of an ETF is computed as the daily weighted average dollar trading volume of its constituent stocks. PRE_t is the ETF's pricing error, measured as the absolute difference between the ETF's net asset value (NAV) and its market price; and OLD_t is the ETF's age, measured by the number of months since its inception date.

We use different panel data models (pooled, ETF fixed effects, year fixed effects, both ETF and year fixed effects) to analyze how well trading variables and ETF characteristics explain cross-sectional and time-series variations in the gap between ETF and underlying liquidity. Because our panel data are subject to bias due to autocorrelation and heteroscedasticity, we report our *t*-statistics using autocorrelation and heteroscedasticity-corrected standard errors (Newey and West, 1987).

Table 2.8. Determinants of the Liquidity Difference between ETFs and Underlying Portfolios

Notes: This table presents regression results of the following model of the difference in liquidity between ETFs and underlying portfolios using Eq. (11). ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Using Difference in Bid-Ask Spread as Dependent Variable

Independent Variables	(1)	(2)	(3)	(4)
Df_LnV	-0.003	0.003	-0.002	0.003
	(-0.77)	(1.06)	(-0.58)	(1.10)
Df_σ^2	34.33	33.45	30.40	34.04
	(0.90)	(0.85)	(0.89)	(0.94)
Df_LnMV	-0.08***	-0.06***	-0.07***	-0.05***
	(-11.72)	(-2.68)	(-11.60)	(-2.44)
Df_LnP	0.21***	0.07	0.074***	0.078**
	(8.83)	(1.47)	(3.17)	(2.16)
PRE	0.43***	0.24*	0.52***	0.25*
	(4.46)	(1.57)	(5.99)	(1.75)
OLD	-0.002***	-0.006***	0.0001	-0.005
	(-3.60)	(-4.60)	(1.87)	(-1.53)
ETF fixed effects	No	Yes	No	Yes
Year fixed effects	No	No	Yes	Yes
Number of Observations	18,903	18,903	18,903	18,903
Adj.R^2	0.027	0.059	0.045	0.064

Panel B. Using Difference in Amihud Illiquidity as Dependent Variable

Independent Variables	(1)	(2)	(3)	(4)
Df_LnV	-14.74***	-15.34***	-14.68***	-15.18***
	(-33.30)	(-33.12)	(-34.05)	(-33.84)
Df_σ^2	2544	2054	2398	2134
	(0.87)	(0.72)	(0.82)	(0.74)
Df_LnMV	12.13***	13.30***	13.53***	14.82***
	(26.33)	(9.28)	(25.09)	(10.25)
Df_LnP	11.89***	-4.20	-2.92*	-2.97
	(6.97)	(-1.22)	(-1.80)	(-0.87)
PRE	66.7***	92.3***	74.6***	92.5***
	(3.12)	(3.87)	(3.55)	(3.90)
OLD	-0.21***	-0.53***	0.08	-0.34*
	(-6.71)	(-8.85)	(2.85)	(-1.76)
ETF fixed effects	No	Yes	No	Yes
Year fixed effects	No	No	Yes	Yes
Number of Observations	18,903	18,903	18,903	18,903
Adj.R^2	0.325	0.348	0.343	0.353

In Table 2.8, we report the results of Eq. (11). Panel A shows that discrepancies in market value, pricing error, and age, as we expected, partly explain the difference in bid-ask spreads between ETFs and their underlying stocks. For example, the negative and significant coefficient of *Df_lnMV* indicates that when an ETF's market value is lower than the average market value of its underlying component stocks, its bid-ask spread tends to be higher than the weighted average spreads of the underlying constituents. The positive and significant coefficient of *PRE* suggests that when an ETF's price deviates from its NAV, it becomes less liquid than its underlying portfolio. Also as we expected, we find that the coefficient of *OLD* is significantly negative when we do not control for the year fixed effects. This implies that ETFs may become more popular with investors as they age, and this popularity helps increase their liquidity relative to that of their underlying portfolios.

Contrary to our expectation, the coefficient of *Df_LnP* is significantly positive in three out of four regression specifications in Panel A. This surprising result could stem from the difference in nature between an ETF price and a stock price. Stoll offers three reasons for including stock price in his model. The first two relate to order processing cost and minimum tick size. The last reason relates to risk: "price is negatively correlated with risk of a stock" (Stoll, 1978, p. 1164). While ETF price may be associated with order processing cost in the same way stock price is, as far as we know, there is no evidence that an ETF's risk is linked to its price.[6]

Panel B of Table 2.8 presents the results of Eq. (11) using the difference in Amihud illiquidity as the dependent variable. We find that the effects of ETF-specific characteristics, *PRE* and *OLD*, are consistent with those in Panel A in that a decrease in an ETF's pricing error or an increase in its age reduces the liquidity gap between the ETF and its underlying stock

[6] Investing in ETFs exposes investors to two main types of risks: investment risk, which is related to return performance, tracking error, and liquidity; and operation risk, that is, the risk of closure or delisting (ETF.com).

portfolio. However, the effect of *Df_ LnMV* on the Amihud illiquidity difference is opposite to that on the bid-ask spread in Panel A. The coefficient of the difference in price, *Df_LnP*, is mixed in sign, and that of the difference in dollar trading volume, *Df_ LnMV*, is negative and significant. Finally, Table 8 shows no significant impact of the difference in return variance, Df_σ^2, on the difference in liquidity.

To assess the relative importance of the determinants in Eq. (11), we rank their contributions to explaining the cross-sectional variation in the difference between ETF and underlying liquidity. Specifically, we consider Eq. (11) as an aggregate model to explain the liquidity gap. Then we regress Eq. (11) cross-sectionally for all days with observations of at least 15 ETFs. We end up estimating 687 daily models, and we average their adjusted R-squareds. For each independent variable, we then compute the difference between the adjusted R-squared of the aggregate model and the adjusted R-squared of a model without that variable. Table 1.9 Panel A reports the results when the dependent variable is the bid-ask spread difference. We find that the discrepancy in market capitalization, *Df_LnMV*, contributes 14.21% to the adjusted R-squared of the aggregate model. The difference in dollar trading volume, *Df_LnV*, is the second most important variable, contributing 6.27%. The ETF pricing error, *PRE*, is not far behind, contributing 6.23%, followed by Df_σ^2, *Df_LnP*, and *OLD* respectively. As a group, these differences in trading characteristics explain about 27% of the cross-sectional fluctuation of the gap between ETF and underlying liquidity, while ETF-specific characteristics explain only 8%.

Table 2.9. Ranking of Determinants of Liquidity Difference between ETFs and Underlying Portfolios
Notes: The table above ranks the determinants of liquidity difference between ETFs and their portfolios according to each determinant's incremental contribution to the adjusted R-squared of the Eq. (11). We estimate the model for all days with a minimum of 15 ETF observations, for a total of 687 daily models with their adjusted R-squareds. *Liquidity_Difference* in the above equation is measured by the difference in the bid-ask spread or in the Amihud illiquidity between an ETF and its underlying portfolio. The adjusted R-squared of the aggregate model is computed as the average of adjusted R-squareds of daily models. To gauge the importance of each independent variable in Eq. (11), we calculate the difference between the adjusted R-squared of the aggregate model and the adjusted R-squared of a model without that variable.

Panel A. Using Difference in Bid-Ask Spread as Dependent Variable

Model Identification	Adjusted R-squared	Variable	Incremental Adj. R-squared by Variable	Importance Ranking
Aggregate Model	44.75%			
Without Df_LnMV	30.54%	Df_LnMV	14.21%	1
Without Df_LnV	38.48%	Df_LnV	6.27%	2
Without PRE	38.52%	PRE	6.23%	3
Without Df_σ^2	40.83%	Df_σ^2	3.92%	4
Without Df_LnP	42.34%	Df_LnP	2.41%	5
Without OLD	42.97%	OLD	1.78%	6

Panel B. Using Difference in Amihud Illiquidity as Dependent Variable

Model Identification	Adjusted R-squared	Variable	Incremental Adj. R-squared by Variable	Importance Ranking
Aggregate Model	73.30%			
Without Df_LnV	27.35%	Df_LnV	45.94%	1
Without Df_LnMV	66.05%	Df_LnMV	7.24%	2
Without PRE	71.17%	PRE	2.13%	3
Without OLD	72.27%	OLD	1.02%	4
Without Df_σ^2	72.39%	Df_σ^2	0.91%	5
Without Df_LnP	72.41%	Df_LnP	0.89%	6

Similarly, Table 2.9 Panel B shows the relative importance of variables in explaining the variation of the difference in Amihud illiquidity between an ETF and its underlying portfolio. The discrepancies in dollar trading volume, *Df_LnV*, and market capitalization, *Df_LnMV*, are the largest contributors to the adjusted R-squared of the model, accounting for 45.94% and 7.24%, respectively. Other variables make much smaller contributions. In sum, we find consistent evidence that differences in dollar trading volume, market capitalization, and ETF pricing error are the most important reasons for discrepancy in liquidity between an ETF and its underlying portfolio.

2.5. Conclusion

Using a sample of U.S. active equity ETFs, we find evidence that the liquidity of these ETFs is consistently lower than that of their underlying portfolios. While diversification is often considered a benefit of investing in ETFs, we find that diversification impairs the liquidity of the underlying portfolio, and this effect can in turn impair the fund's liquidity through the creation/redemption mechanism. The gap between an ETF's liquidity and that of its underlying portfolio depends both on its trading characteristics, including dollar trading volume, return volatility, market value, and trading price, and on portfolio-specific characteristics like ETF pricing error and ETF age.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Son Pham
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Name of Research Output and full reference:	
Son D.P., Ben, R.M., Nhut, H.N., and Nuttawat, V. (2020). The liquidity of active ETFs. Global Finance Journal (Forthcoming). https://doi.org/10.1016/j.gfj.2020.100572.	
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CHAPTER THREE: ESSAY TWO

This chapter presents the second essay which examines the extent to which ETF trading costs can be minimized via a systematic trading schedule. A brief overview of the key findings is presented in Section 3.1. Section 3.2 reviews related literature. Section 3.3 presents the data and the methodologies used in the essay. Section 3.4 reports the core results and related discussion. Section 3.5 concludes this chapter. Appendices to this chapter and the essay's reference list are provided at the end of thesis.

Predicting ETF Liquidity

Abstract

A substantial amount is incurred in ETF transaction costs each year. This paper examines a vector autoregressive (VAR) model's performance and other naïve models to time trades in 1,350 ETFs over the 2011 to 2017 period. We find varied spread savings for large and retail ETF traders by timing transactions. A large ETF trader can save 7.40% of ETF spread costs, whereas trading at the market closing time would be optimal for a retail ETF trader to reduce spread costs. The spread savings for large ETF traders are diverse across ETF sectors and depend on the spread volatility.

JEL Classification Codes: G11, G23
Keywords: ETFs; Liquidity; Bid-Ask Spread; Forecasting

3.1. Introduction

Transaction costs are an essential determinant of investors' returns (e.g., French, 2008). As a result, several papers have investigated approaches to minimizing spread costs in stock transactions (Taylor, 2002; Wald and Horrigan, 2005; Groß-KlußMann and Hautsch, 2013). While an exchange-traded fund (ETF) is traded on the stock exchange like a stock and has many common liquidity determinants, there are critical differences between ETF and stock liquidity. First, trading costs associated with ETFs are lower than individual stocks (Gastineau, 2001). Second, information asymmetry present in ETFs is lower than for individual stocks, leading to lower adverse selection costs (Chelley-Steeley and Park, 2010). We contribute to the literature by considering the extent to which traders can minimize transaction costs in trading ETFs via a systematic trading schedule, which is essential for several reasons.

First, ETFs are an important and growing component of financial trading. According to Financial Times, by 2016, ETFs accounted for approximately 30 percent of all US equity trading by value[7]. The average daily transaction value of U.S. ETFs was USD 110.79 billion[8] as of Q3 2020. Second, due to low transaction costs and information availability, high-frequency trading has become prevalent for ETFs (Ben-David, Franzoni, and Moussawi, 2014). As high-frequency traders trade a lot with marginal expected gain for each trade, minimizing ETF bid-ask spread should be their key priority. Third, while some ETFs have low bid-ask spreads, which are likely to have little impact on ETF investors, many ETFs do not. The ETF bid-ask spreads in our sample are diverse, ranging from 0.03% at the 1st percentile to 4.42% at the 99th percentile with an average of 0.44%[3]. The cost of trading ETFs is an essential component of the return many ETF investors receive. Finally, although investors can pick an ETF with a low bid-ask spread among different ETFs tracking the same index, this strategy is not without cost. Khomyn, Putniņš, and Zoican, (2020) find that an ETF with greater market liquidity tends to charge higher management fees than its peers. Therefore, reducing transaction costs is crucial for ETF investors as they face a trade-off between liquidity and prices when investing in ETFs.

We use an unrestricted vector autoregressive (VAR) model based on Taylor's (2002) model to predict intraday ETF bid-ask spreads for a large sample of 1,350 US ETFs between January 2011 and December 2017. In our VAR model, we assume ETF bid-ask spread is dependent on its past spread, past degree of return volatility, past level of trade volume, and past level of trade intensity. These trading characteristics are essential determinants of ETF liquidity, as documented in Agrrawal and Clark (2009), Calamia, Deville, and Riva (2013), and Ivanov (2017). We find that this model is superior to a moving average model in predicting short-term ETF bid-ask spreads. Moreover, splitting and timing trades based on predictions

[7] Financial Times (2017). ETFs are eating the US stock market. *Retrieved from*: https://www.ft.com/content/6dabad28-e19c-11e6-9645-c9357a75844a.
[8] *Retrieved from*: https://www.nyse.com/etf/exchange-traded-funds-quarterly-report
[3] For comparison, the average bid-ask spread of US stocks listed on NYSE, NASDAQ, and AMEX between 2003 and 2015 is 0.82% as shown in Abdi and Ranaldo (2017). Bid-ask spreads of several foreign exchanges range from 0.03% to 0.2% as of 2012 (Blackrock, 2012).

from this model brings meaningful transaction cost savings for large ETF traders compared to the other trading schedules.

We assess the VAR model's quality by considering the spread forecasts' deviation relative to the actual figures. Using Mariano and Diebold's (1995) test and Harvey, Leybourne, and Newbold's (1997) test, we find that the VAR model generates better forecasts than a moving average prediction model. Furthermore, we find the model's performance is dependent on ETF characteristics and macro-economic conditions.

The ETF characteristics, sector, and style affect the spread forecast accuracy. Forecast errors are broader when an ETF is more volatile in return and smaller in size. The VAR model produces better forecasts for ETFs belonging to the Allocation and Fixed Income sectors. Among equity ETFs, the VAR model has lower forecast errors for ETFs investing in large-cap stocks.

The predictability of a forecasting model might be dependent on macro-economic conditions in certain periods (Fama and French, 1989; Schwert, 2002). Using a set of macro-economic variables representing market-wide uncertainty and financial risk, we find that those factors impact the ability to predict ETF bid-ask spreads using the VAR model. The model's forecast errors increase with market uncertainty measured by the range of market return and market return volatility. Moreover, an increase in default risk in the market also dampens the forecast accuracy.

We also estimate the economic significance of this VAR model from the perspective of both large and retail ETF traders[9] who use its bid-ask spread predictions to time their trades. The average executed bid-ask spread of a hypothetical ETF trader using bid-ask spread

[9] We define a large ETF trader as traders who trade a large number of ETF shares for either liquidity reasons or possessing private information. Retail ETF trader is defined as traders who trade a small number of ETF shares and do not have private information.

forecasts from the VAR model to schedule her trade is compared to that using other trading schedules. For a large ETF trader who wants to hide her trade motivation by splitting the orders over the trading day, the VAR trading schedule is superior to other trading schedules in terms of spread saving. We find that the average executed bid-ask spread using the VAR model to schedule trade is 7.4% and 8.29% lower than that using a naïve trading schedule and a moving average trading schedule, respectively. The spread discount for a large ETF trader using the VAR trading schedule is as high as 30.81% compared to the daily average bid-ask spread of ETFs. However, for a retail ETF trader who does not need to split his order, we reveal that trading would be optimal to reduce bid-ask spread cost once at the close. The average closing bid-ask spread of ETFs is 45% lower than the average executed bid-ask spread using the VAR trading schedule. Nevertheless, there is a non-execution risk for orders submitted at the market close.

The spread saving of the VAR trading schedule compared to a naïve trading schedule for ETFs is lower than that for stocks as documented by Taylor (2002) and Groß-KlußMann and Hautsch (2013)[10]. We expect that spread volatility can partly explain why the transaction cost savings by splitting and timing trades are lower for ETFs than for stocks. If bid-ask spreads are unchanged throughout the day, there is no need to save spread costs by timing transactions. Expected spread savings by timing trades should be dependent on spread volatility. ETFs are diversified portfolios where company-specific risks are canceled out, ETFs should have lower volatility in return and spread than stocks. We find that spread volatility is positively correlated with spread saving, which supports our explanation. Furthermore, while the average spread saving is low, it is widely diverse across ETF sectors. The benefit of timing trades is lower for

[10] Taylor (2002) finds that using predictions of bid-ask spreads from a VAR model can save up 34% of spread costs for LSE stocks. Groß-KlußMann and Hautsch (2013) use a long-memory autoregressive conditional Poison model to predict the bid-ask spreads of 4 US mid-cap stocks and find that the predictions from their model can help traders saving 8.4% to 10.9% of spread costs.

less volatile ETF sectors like Fixed Income, and Tax Preferred while higher for more volatile ETF sectors such as Equity and Commodities.

Our research makes several contributions to the current literature of ETF liquidity. First, our present work is the first to predict ETF liquidity to the best of our knowledge. Compared to individual securities, ETFs provide lower trading costs and have lower information asymmetry (Hedge and McDermott, 2004; Chelley-Steeley and Park, 2010). Deriving a model to predict intraday ETF liquidity could bring crucial implications for market participants. For portfolio managers, better forecasts of expected trading costs improve the capacity to implement portfolio strategies and monitor trade execution quality. Traders, especially high-frequency traders, can take advantage of mispricing in the ETF market, even if these inefficiencies last for just a few minutes or seconds. As high-frequency traders tend to trade a lot, they are concerned with transaction costs, and forecasting ETF liquidity should be prominent.

Second, our research examines the degree to reduce the ETF transaction costs using ETF bid-ask spread predictions. We find the VAR model helps large ETF traders save their spread costs compared to other trading schedules. However, it is optimal for retail ETF traders to trade at the close to minimize spread costs. The benefit of splitting and timing trades using the VAR trading schedule compared to using naïve trading schedule tends to be lower for less volatile ETF sectors like Fixed Income, and Tax Preferred while higher for more volatile ETF sectors such as Equity and Commodities. Our finding of a positive relationship between transaction cost-saving and spread volatility is new to the literature. It provides unique insight for traders and researchers looking to minimize ETF transaction costs.

Third, our research investigates the effect of ETF characteristics and market-wide uncertainties on the VAR model's forecast accuracy. Some ETF sectors like Allocation or Fixed

Income have lower forecast errors than others when using the VAR model to predict their intraday bid-ask spreads. The dependency of the forecast errors on ETF and market-wide volatility also highlights this prediction model's limitations. When liquidity has a great chance of dry up in the market, predictions of ETF intraday liquidity using the VAR model are less reliable.

The remainder of the paper is structured as follows. Section 3.2 reviews related literature. Section 3.3 is about data and methodologies used in this paper. Section 3.4 documents the empirical results of using the VAR model to predict ETF bid-ask spreads. Section 3.5 concludes the article.

3.2. Literature review

While literature is replete with research on liquidity, predicting liquidity receives lesser attention. Huang and Stoll (1994) indicate the price impact of trading stocks using a two-equation econometric model. They assume that quote return is a function of several factors, including past quote return, market return, and inventory change. Breen, Hodrick, and Korajczyk (2002) predict the price impact of trading stocks based on net turnover[11]. They find that the coefficient of the price impact in their model is dependent on the adverse selection cost, the non-information-based costs of market making, and the extent of shareholder heterogeneity of stocks.

In terms of predicting bid-ask spreads, Huang and Masulis (1999) use a trivariate VAR to model bid-ask spread, competition, and return volatility in foreign exchange markets. Based on Huang and Masulis's (1999) framework, Taylor (2002) develops an unrestricted VAR model

[11] Breen et al (2002) define Net turnover as buyer-initiated volume less seller-initiated volume as a fraction of shares outstanding

to predict quoted bid-ask spreads of stocks on the London Stock Exchange. In this model, Taylor expects the stock bid-ask spread as a function of five lagged factors. These determinants are lagged bid-ask spread, dealer competition, return volatility, trading volume, and trade intensity. Taylor (2002) demonstrates that his model can efficiently project bid-ask spreads of stocks and save transaction costs by about 34% for traders. Recently, Groß-KlußMann and Hautsch (2013) use a long-memory autoregressive conditional Poison model to predict the bid-ask spreads of 4 U.S. mid-cap stocks and find that the predictions from their model can help traders saving 8.4% to 10.9% of spread costs.

Variables used to predict stock bid-ask spread in Taylor's (2002) model are well-known in microstructure literature to affect stock liquidity. For instance, Stoll (2000) explains stock liquidity variation on several stock trading characteristics, including return volatility, dollar-trading volume, and the number of trades. Regarding intraday liquidity, McInish and Wood (1992) develop a model to explain intraday stock bid-ask spread based on intraday trading activity, intraday risk level (stock volatility), the amount of information coming to the market, and the level of competition. Lee, Mucklow, and Ready (1993) study the effect of volume on the stock depth and spread using intraday data. They find that higher volume during a given interval should be associated with a broader spread and lower depth at the end of the interval during a trading day.

Like stock bid-ask spread, the ETF bid-ask spread varies with its trading characteristics. Agrrawal and Clark (2009) find that the ETF bid-ask spread inversely correlates with trading volume and market capitalization. Calamia, Deville, and Riva (2013) reveal that ETF bid-ask spread decreases with the ETF trading volume and increases with ETF return volatility. Using high-frequency data, Ivanov (2017) documents that factors including trading activity, risk, information, and competition influence ETF intraday bid-ask spread. These findings support that variables used in Taylor's (2002) model could be useful to predict ETF liquidity.

3.3. Data and Methodologies

3.3.1. Data

We conduct our research using intraday data of 1,350 US ETFs during the period between 2011 and 2017. First, we obtain data on all exchange-traded funds from the CRSP stock database identified by their share code of 73. Then we extract intraday trading data of these ETFs from Thomson Reuters Tick History (TRTH). To be consistent with prior literature when studying stocks' intraday activities, we examine ETFs' trading activity between 9:30 am to 4:00 pm.

To screen intraday data files for mistakes, we employ a similar screening procedure used previously by Huang and Stoll (1996) and Bessembinder (1999). We exclude:

- Quotes if either the ask or bid price is less than or equal to zero;

- Quotes if either the ask size or bid size is less than or equal to zero;

- Quotes if the bid-ask spread is less than zero;

- Quotes and trades before the open and after the close;

- Trades if the price or volume is less than or equal to zero;

- The trade price, p_t, if $|(p_t - p_{t-1})/p_{t-1}| > 0.5$;

- The ask price, a_t, if $|(a_t - a_{t-1})/a_{t-1}| > 0.5$;

- The bid price, b_t, if $|(b_t - b_{t-1})/b_{t-1}| > 0.5$.

We source other ETF characteristics using data from CRSP and Morningstar. We get daily and the monthly bid-ask spread, trading volume, price, return, and shares outstanding of

ETFs from CRSP. Qualitative characteristics such as ETF sectors and investment categories are from Morningstar.

3.3.2. Methodologies

We use Taylor's (2002) model framework to predict the quoted bid-ask spread of 1,350 ETFs from 01 Jan 2011 to 29 December 2017. Following Taylor's (2002) model, we also use a frequency of 5 minutes to calculate variables in the VAR model. We estimate the following VAR model:

$$\begin{pmatrix} s_{i,t} \\ \sigma_{i,t} \\ V_{i,t} \\ I_{i,t}^{T} \end{pmatrix} = \begin{pmatrix} \beta_1(L) & \beta_2(L) & \beta_3(L) & \beta_4(L) \\ \beta_5(L) & \beta_6(L) & \beta_7(L) & \beta_8(L) \\ \beta_9(L) & \beta_{10}(L) & \beta_{11}(L) & \beta_{12}(L) \\ \beta_{13}(L) & \beta_{14}(L) & \beta_{15}(L) & \beta_{16}(L) \end{pmatrix} \begin{pmatrix} s_{i,t-1} \\ \sigma_{i,t-1} \\ V_{i,t-1} \\ I_{i,t-1}^{T} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,i,t} \\ \epsilon_{2,i,t} \\ \epsilon_{3,i,t} \\ \epsilon_{4,i,t} \end{pmatrix} \tag{1}$$

where $s_{i,t}$ is the quoted bid-ask spread of ETF *i* measured at the end of each 5-minute time interval starting from 9:35 am and ending at 4:00 pm of the trading day; $\sigma_{i,t}$ is the standard deviation of midpoint quotes during each 5-minute time interval[12]; $V_{i,t}$ is the trading volume during each 5-minute time interval; $I_{i,t}^{T}$ is the number of trades during each 5-minute time interval; $\beta_1(L)$ to $\beta_{16}(L)$ are lag polynomials each of order *p*, and $\epsilon_{k,i,t}$ is the error term.

Following Taylor's (2002), we impose a lag length equal to one trading day in the model[13] , and the remaining lag order is estimated using the Akaike information criterion

[12]. For instance, the first $\sigma_{i,t}$ of each day is calculated as the standard deviation of midpoint quotes between 9:30 am to 9:35 am

[13] This specification accounts for periodic components in the variables. As a trading day can be divided into 78 5-minute intervals, so we use a lag order of 78 in our VAR model to account for periodicity. Descriptive statistics of ETF quoted bid-ask spread and effective spread and the evidence of their periodicities can be found in Appendix

(AIC). Upon completion of each estimation of the model, the model forecasts the liquidity at 1-step ahead (5 minutes head), 2-step ahead (10 minutes ahead), 3-step ahead (15 minutes ahead), 4-step ahead (20 minutes ahead), and 5-step ahead (25 minutes ahead).

Consistent with Taylor's (2002) model, we use de-meaned variables for equation (1). The de-meaned variables are the difference between the variables and their mean values over the sample period. The whole sample period starts at 9:30 am on 03 Jan 2011 and ends at 4:00 pm on 29 December 2017. Each day has 390 minutes of trading time that equals 78 5-minute time intervals. The first in-sample data used starts at 9:35 am on 03 Jan 2011 and ends at 4:00 pm on 07 Jan 2011. Estimation of equation (1) using this sample data will generate bid-ask spread forecasts for 9:35 am, 9:40 am, 9:45 am, 9:50 am, and 9:55 am on 10 January. The second in-sample data starts at 10:05 am on 03 January and ends at 10:00 am on 10 January. Thus, the in-sample data is rolled over every 30 minutes with a fixed estimation window of 5 trading days.

3.4. Empirical Results

This section presents the empirical results of using the VAR model in predicting intraday ETF bid-ask spread. Sub-section 3.4.1 assesses the forecast quality of the model using various tests. Sub-section 3.4.2 examines the determinants of the model's forecast errors. Sub-section 3.4.3 gauges the economic benefit derived from a trading strategy based on the model's prediction results. Sub-section 3.4.4 investigates the effect of spread volatility on the spread saving derived from the VAR model.

B.1 and Appendix B.2, respectively. Appendix B.3 plots the intraday pattern of ETF quoted bid-ask spread and effective spread.

3.4.1. Assessing forecast accuracy

The means of the variables used in equation (1) are shown in Table 3.1. Panel A shows these statistics by the ETF sector. Fixed Income has the lowest average bid-ask spreads among various ETF sectors, followed by Tax Preferred and Allocation. Conversely, Convertibles and Alternative have the highest average bid-ask spreads, respectively. In Panel B, we group ETFs into liquidity quintiles based on their average quoted bid-ask spreads. The mean bid-ask spread ranges from 22.52 basis points for the most liquid ETFs to 77.47 basis points for the least liquid ETFs.

Table 3.1. Summary of Variables Used in the VAR Model

Notes: This table presents the descriptive statistics of variables used in the VAR model to predict the ETF bid-ask spread. $s_{i,t}$ is quoted bid-ask spread of ETF *i* measured at the end of a 5-minute time interval *t* starting from 9:35 am and ending at 4:00 pm of the trading day; $\sigma_{i,t}$ is the standard deviation of midpoint quotes during each 5-minute time interval; $V_{i,t}$ is the trading volume during each 5-minute time interval; $I_{i,t}^{T}$ is the number of trades during each 5-minute time interval. Panel A reports the average values of these variables by different ETF sectors. Panel B shows the average values for different liquidity-ranked groups with L_1 being the most liquid group and L_5 the least liquid group.

Panel A. By ETF sector

ETF Sector	$s_{i,t}$ (in bps)	$V_{i,t}$	$\sigma_{i,t}$ (in pct.)	$I_{i,t}^{T}$
Allocation	40.03	171	2.04	0.27
Alternative	50.61	2,888	4.63	3.66
Commodities	43.94	498	3.67	0.69
Convertibles	48.89	489	2.91	0.85
Equity	45.18	634	2.76	0.83
Fixed Income	31.93	547	2.35	0.93
Tax Preferred	34.28	83	1.98	0.20
Average	43.65	988	3.00	1.31

Panel B. By liquidity quintiles

Liquidity Rank	$s_{i,t}$ (in bps)	$V_{i,t}$	$\sigma_{i,t}$ (in pct.)	$I_{i,t}^{T}$
L_1 (most liquid)	22.52	2,689	2.81	3.61
L_2	28.55	1,495	4.21	1.77
L_3	40.97	245	2.12	0.48

L_4	49.91	142	2.49	0.30
L_5 (least liquid)	77.47	50	3.25	0.12
Average	43.65	988	3.00	1.31

In Taylor's (2002) work, the VAR forecasts' quality is compared to the quality of predictions generated by a simple random walk model. He assumes that "the cumulative spreads follow a random walk while the spread itself is a white noise process with positive mean". Therefore, this model "generates forecasts equal to mean of the in-sample period spread" (Taylor, 2002, p. 807). Following Taylor's (2002) paper, we compare the mean squared forecast error (MSFE) and the mean absolute forecast error (MAFE) of the VAR model (M2) with this simple moving average model (M1). The formulas for MAFE and MSFE are the following:

$$MAFE=\frac{1}{T}.\sum_{t=1}^{T} | y_{t+h} - y'_{t+h}| \qquad (2)$$

$$MSFE=\frac{1}{T}.\sum_{t=1}^{T}(y_{t+h} - y'_{t+h})^2 \qquad (3)$$

where y_{t+h} is the h-step ahead forecast of ETF bid-ask spread at time t and y'_{t+h} is the realized value of the ETF bid-ask spread at the time ($t+h$).

Table 3.2 presents a summary of the comparison between forecast error metrics of M1 and M2. Panel A shows the proportion of ETFs, which have lower MAFE and MSFE using the VAR model than the moving average model. In general, both MAFE and MSFE comparisons indicate that using the VAR model, M2, generates better results than the moving average model, M1, for short-term forecasts (h=1, 2) for most ETFs. Consistent with Taylor's (2002) findings, we find that the VAR model's benefit to estimate bid-ask spreads for ETFs is most apparent under the 1-step forecasts and the MAFE criteria. In Panel A, 78.55% of ETFs in our sample exhibit lower MAFE when the VAR model predicts the next 5 minutes bid-ask spreads compared to the moving average model. The VAR model's outperformance remains relatively high for the 10-minute (i.e., 2-step) prediction horizon, with 70.29% of ETFs showing lower MAFE. The VAR model's performance relative to that of the moving average model in MAFE reduces substantially after the 2-step forecast. The results of MSFE are less impressive as only 54.2% of ETFs have lower MSFE using M2 versus M1 for 1-step ahead bid-ask spread prediction.

Table 3.2 Panel B shows the average values of MAFE and MSFE for M1 and M2. Overall, the average values of MAFE and MSFE for M2 are higher than for M1, except for the 1-step forecast ahead. The average MAFE at the 1-step horizon for M2 is 0.00145, which is approximately 56% smaller than for M1.

To statistically test the predictive accuracy of M1 and M2-based forecasts, we first use the Diebold-Mariano test (1995), calculated through the following steps:

$$d=\frac{1}{N}. \sum_{n=1}^{N}[\, g(e_{t+h}) - g(e'_{t+h}) \,] \tag{4}$$

$$DM=\frac{d}{(\sigma_d^2/N)^{1/2}} \tag{5}$$

where $g(e_{t+h})$ and $g(e'_{t+h})$ are the loss functions of M1 and M2, respectively; N is the number of rolling out-of-sample forecasts; σ_d^2 is the variance of d and *D.M.* is the Diebold-Mariano statistic. We use Diebold-Mariano to test the null hypothesis that the VAR model forecasts, M2, are of the same or lower quality than forecasts from the moving average model, M1. The alternative is that forecasts from M2 are better than forecasts from M1.

Table 3.2. Assessing Forecast Quality Using MAFE and MSFE

Notes: This table presents the statistics of mean absolute forecast error (MAFE) and mean squared forecast error (MSFE) of the VAR model (M2) and a moving average model (M1) to predict ETF bid-ask spread. Panel A shows the number and the percentage of ETFs having lower MAFE or MSFE using M2 compared to M1. Panel B shows the average values of MAFE and MSFE for M1 and M2.

Panel A. ETFs with Better h-Step Forecast Using the VAR-Model

	h: the number of periods ahead forecast				
	1	*2*	*3*	*4*	*5*
Number of ETFs have lower MAFE using M2 than M1	1,060	949	726	526	375
Percentage of ETFs have lower MAFE using M2 than M1	78.55%	70.29%	53.85%	38.96%	27.81%
Number of ETFs have lower MSFE using M2 than M1	732	488	301	195	145
Percentage of ETFs have lower MSFE using M2 than M1	54.20%	36.13%	22.30%	14.47%	10.73%
Total number of ETFs	1,350	1,350	1,350	1,350	1,350

Panel B. Average Values of MAFE and MSFE for M1 and M2

		h: the number of periods ahead forecast				
		1	*2*	*3*	*4*	*5*
	M1	0.00258	0.00256	0.00256	0.00256	0.00256
Average value of MAFE	M2	0.00145	0.00260	0.02344	0.81151	37.54006
	M1	0.00017	0.00017	0.00017	0.00017	0.00017
Average value of MSFE	M2	0.00222	0.64134	1.1172	2.1895	4.6879

Table 3.3 Panel A gives the proportion of stocks for which the forecasts generated by M2 are significantly better or worse than the forecasts produced by M1 using the Diebold-Mariano Test at the 5% significance level. Consistent with findings in the previous section, the VAR model, M2, is superior to the moving average model, M1, especially for 1- or 2-step ahead forecasts and using the MAFE as the loss function. In detail, 72.41% of ETFs experience significantly lower MAFE using M2 to predict their 1-step bid-ask spreads compared to using M1. For 2-step ahead forecasts, the proportion of ETFs with lower MAFE using M2 decreases to 56.95%.

The results of the Diebold-Mariano Test using MSFE as forecast error criteria are less dramatic. There are 29.59% of ETFs having significantly lower MSFE using M2 to predict their 1-step bid-ask spreads compared to using M1. For 4-step and 5-step ahead prediction, the proportion of ETFs with higher MSFE using M2 bypasses ETFs' proportion with significantly lower MSFE using M2. This indicates that M2 becomes less efficient than M1 to predict bid-ask spreads for longer horizons.

Harvey, Leybourne, and Newbold (1997) (HLN) suggest that the D.M. test can be improved by making a bias correction to the D.M. test statistic and comparing the corrected statistic with a Student-*t* distribution with (*n-1*) degrees of freedom, rather than the standard normal. However, this test is designed only for the MSFE but not MAFE.

Table 3.3 Panel B shows the proportion of ETFs. The forecasts generated by M2 are significantly better or worse than the forecasts produced by M1 using the HLN test at the 5% significance level MSFE as the forecast accuracy metric. The HLN test results are consistent with Mariano-Diebold Test and imply that M2 is superior to M1 for 1- or 2-step forecasts. The proportions of ETFs which record significantly lower MSFE using M2 using the HLN test are 35.71% and 19.69% for 1-step and 2-step ahead forecasts, respectively.

Table 3.3 Comparing Forecast Quality

Notes: This table presents the results of the prediction accuracy test for the MAFE and MSFE derived from the VAR model (M2), and a moving average model (M1) to predict ETF bid-ask spread. Panel A reports the percentage of ETFs which have significantly lower (higher) MAFE or MSFE using M2 compared to using M1 indicated by Mariano-Diebold (1995) test. Panel B reports the percentage of ETFs that have significantly lower (higher) MSFE using M2 compared to using M1 indicated by Harvey, Leybourne, and Newbold (HLN) (1997) test.

Panel A. Using Diebold-Mariano Test (1995)

	h: the number of periods ahead forecast				
	1	*2*	*3*	*4*	*5*
Proportion of ETFs have significantly *lower* MAFE using M2 than M1	72.41%	56.95%	38.53%	25.55%	16.73%
Proportion of ETFs have significantly *higher* MAFE using M2 than M1	0.71%	0.99%	5.08%	10.16%	15.46%
Proportion of ETFs have significantly *lower* MSFE using M2 than M1	29.59%	15.07%	7.42%	4.29%	2.73%
Proportion of ETFs have significantly *higher* MSFE using M2 than M1	1.09%	2.58%	7.73%	12.41%	15.93%

Panel B. Using HLN (1997) Test

	h: the number of periods ahead forecast				
	1	*2*	*3*	*4*	*5*
Proportion of ETFs have significantly *lower* MSFE using M2 than M1	35.71%	19.69%	10.23%	6.07%	4.30%
Proportion of ETFs have significantly *higher* MSFE using M2 than M1	1.91%	3.39%	5.01%	6.14%	6.92%

3.4.2. Determinants of forecast errors

The effects of stock sectors and stock characteristics on the predictability of return forecasting models have been examined in literature (Phan, Sharma, and Naryan, 2015; Lawrenz and Zorn, 2017). For instance, Phan, Sharma, and Naryan (2015) find that stock return predictability based on the oil price is sector-dependent and linked to specific sector characteristics such as book-to-market ratio, dividend yield, price-earnings ratio, and trading volume. This section investigates the determinants of bid-ask spread predictability, including both ETF characteristics and market condition variables.

We use the out-of-sample forecast errors as proxies for the VAR model in predicting bid-ask spread. ETFs in the sample are categorized into seven broad sectors, including Allocation, Alternative, Commodities, Convertibles, Equity, Fixed Income, and Tax Preferred. Besides, Equity ETFs are further divided into nine sub-sectors based on their investment style following Morningstar classification. The ETF quantitative characteristics examined include ETF return volatility, ETF dollar trading volume, and ETF market value. Since these characteristics affect the ETF bid-ask spread in literature[14], they are likely to affect the forecast errors of models predicting bid-ask spread.

To assess the effect of ETF characteristics on forecast errors of the VAR model, we use the following equations:

[14] See Agrrawal and Clark (2009), Rompotis (2010), Calamia, Deville, and Riva (2013).

$$FOR\_ERROR_{E,t} = \alpha + \beta_1 RETVAR_{E,t} + \beta_2 LDVOL_{E,t} + \beta_3 LogMV_{E,t} + \beta_4 Allocation_{E,t} + \beta_5 Alternative_{E,t} + \beta_6 Commodities_{E,t} + \beta_7 Convertibles_{E,t} + \beta_8 Equity_{E,t} + \beta_9 FixIn_{E,t} + \epsilon_t \quad (6)$$

$$FOR\_ERROR_{E,t} = \alpha + \beta_1 RETVAR_{E,t} + \beta_2 LDVOL_{E,t} + \beta_3 LogMV_{E,t} + \beta_4 Large\_Blend_{E,t} + \beta_5 Large\_Growth_{E,t} + \beta_6 Large\_Value_{E,t} + \beta_7 Mid\_Blend_{E,t} + \beta_8 Mid\_Growth_{E,t} + \beta_9 Mid\_Value_{E,t} + \beta_{10} Small\_Blend_{E,t} + \beta_{11} Small\_Growth_{E,t} + \epsilon_t \quad (7)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of dollar trading volume of ETF; $LogMV_{E,t}$ is the logarithm of market value of ETF. $Allocation_{E,t}$, $Alternative_{E,t}$, $Commodities_{E,t}$, $Converitbles_{E,t}$, $Equity_{E,t}$, $FixIn_{E,t}$ are dummy variables accounting for different ETF broad sectors. Each dummy variable takes the value of 1 if the ETF belongs to the designated sector, and 0 otherwise. $Large\_Blend_{E,t}$, $Large\_Growth_{E,t}$, $Large\_Value_{E,t}$, $Mid\_Blend_{E,t}$, $Mid\_Growth_{E,t}$, $Mid\_Value_{E,t}$, $Small\_Blend_{E,t}$ and $Small\_Growth_{E,t}$ are dummy variables accounting for different equity styles of ETF. Each dummy variable takes the value of 1 if the ETF belongs to the designated equity style and 0 if otherwise. The reference sector in equation (6) is Tax Preferred and the reference style in equation (7) is Small Value.

Table 3.4. Effect of ETF Characteristics on Forecast Errors

Notes: Table 3.4 Panel A presents the regression results of the following model:

$$FOR\_ERROR_{E,t}=\alpha+\beta_1 RETVAR_{E,t}+\beta_2 LDVOL_{E,t}+\beta_3 LogMV_{E,t}+\beta_4 Allocation_{E,t}+\beta_5 Alternative_{E,t} + \beta_6 Commodities_{E,t} + \beta_7 Convertibles_{E,t} + \beta_8 Equity_{E,t} + \beta_9 FixIn_{E,t} + \epsilon_t \quad (6)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of dollar trading volume of ETF; $LogMV_{E,t}$ is the logarithm of market value of ETF. $Allocation_{E,t}$, $Alternative_{E,t}$, $Commodities_{E,t}$, $Converitbles_{E,t}$, $Equity_{E,t}$, $FixIn_{E,t}$ are dummy variables accounting for different ETF sectors. Each dummy variable takes the value of 1 if ETF belongs to the designated sector and 0 otherwise. The reference sector is Tax Preferred.

Table 4 Panel B presents the regression results of the following model:

$$FOR\_ERROR_{E,t} = \alpha + \beta_1 RETVAR_{E,t} + \beta_2 LDVOL_{E,t} + \beta_3 LogMV_{E,t} + \beta_4 Large\_Blend_{E,t} + \beta_5 Large\_Growth_{E,t} + \beta_6 Large\_Value_{E,t} + \beta_7 Mid\_Blend_{E,t} + \beta_8 Mid\_Growth_{E,t} + \beta_9 Mid\_Value_{E,t} + \beta_{10} Small\_Blend_{E,t} + \beta_{11} Small\_Growth_{E,t} + \epsilon_t \quad (7)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of dollar trading volume of ETF; $LogMV_{E,t}$ is the logarithm of market value of ETF. $Large\_Blend_{E,t}$, $Large\_Growth_{E,t}$, $Large\_Value_{E,t}$, $Mid\_Blend_{E,t}$, $Mid\_Growth_{E,t}$, $Mid\_Value_{E,t}$, $Small\_Blend_{E,t}$ and $Small\_Growth_{E,t}$ are dummy variables accounting for different equity styles of ETF. Each dummy variable takes the value of 1 if ETF belongs to the designated equity style and 0 otherwise. The reference style is Small Value.

***, **, and * represent statistical significance at the 1%, 5% and 10%, respectively.

Panel A. Effect by ETF sector			*Panel B. Effect by ETF equity style*		
	MAFE	Ln(MSFE)		MAFE	Ln(MSFE)
RETVAR	0.029***	34.3***	RETVAR	0.063***	71.12***
	(19.44)	(128.7)		(27.69)	(135.97)
LDVOL	-0.122*	0.052***	LDVOL	0.158**	0.057***
	(-1.74)	(42.99)		(2.33)	(36.63)
LogMV	-0.842***	-0.21***	LogMV	-0.361***	-0.12***
	(-6.63)	(-95.01)		(-3.00)	(-44.55)
Allocation	2.502	0.627***	Large_Blend	2.454***	-0.257***
	(1.55)	(22.18)		(2.95)	(-13.44)
Alternative	6.361***	0.699***	Large_Growth	3.314***	-0.048***
	(4.63)	(29.08)		(3.73)	(-2.37)
Commodities	12.4***	1.390***	Large_Value	1.983**	-0.075***
	(6.50)	(41.69)		(2.34)	(-3.84)
Convertibles	12.9	1.776***	Mid_Blend	4.191***	0.358***
	(1.57)	(12.36)		(4.61)	(17.12)
Equity	7.236***	1.203***	Mid_Growth	3.166***	0.115***
	(5.57)	(52.93)		(3.13)	(4.96)
FixIn	2.141	0.218***	Mid_Value	2.138**	0.143***
	(1.60)	(9.32)		(2.30)	(6.7)
Intercept	17.6***	-13.7***	Small_Blend	2.634**	0.039*
	(10.70)	(-476)		(2.51)	(1.63)
			Small_Growth	3.542**	-0.015
				(2.57)	(-0.47)
			Intercept	9.902***	-13.9***

				(7.88)	(-480)
Obs.	806,242	806,242	Obs.	483,519	483,519
Adj. R^2	0.0012	0.0742	Adj. R^2	0.0018	0.0554

The equations (6) and (7) are reported in Table 3.4 Panel A and B. In Panel A, we find that the VAR model's predictability is significantly dependent on ETF characteristics. Forecast errors measured by either *MAFE* or *Ln(MSFE)* are positively correlated with ETF return volatility, *RETVAR*, and negatively correlated with ETF market value, *LogMV*. This implies that the VAR model's predictability in forecasting ETF bid-ask spread is better for ETFs with lower return variance and larger market capitalization. The evidence of the effect of ETF dollar trading volume, *LDVOL* on the model's forecast errors, is mixed. We find that the trading activity is positively correlated with *Ln(MSFE)* and negatively correlated with *MAFE*.

Moreover, our results also suggest that the predictability of the VAR model is sector-dependent and style-dependent. The forecast errors of the model measured by either *MAFE* or *Ln(MSFE)* are largest for ETFs belonging to Commodities, Equity, and Alternative sectors, as shown in Panel A. In Panel B, the regression results using *MAFE* indicate that the VAR model predicts better the bid-ask spread of ETFs investing in large-cap stocks. When *Ln(MSFE)* is used, we find that the M2 model's forecast errors tend to be lower for large-cap than mid-cap or small-cap stocks.

Fama and French (1989) and Schwert (2002) find that their models predict stock market return is time-variant. For instance, Schwert (2002) finds that the relation between the aggregate dividend yield and future stock market return changes significantly over time. These studies imply that the predictability of a forecasting model may depend on the macro-economic environment. To account for the effect of macro-economic variables on the predictability of the VAR model in forecasting ETF bid-ask spread, we regress the following equation:

$$FOR\_ERROR_t = \alpha + \beta_1 WRET_t + \beta_2 WARET_t + \beta_3 WVARRET_t + \beta_4 ShorRate_t + \beta_5 TermSpread_t + \beta_6 DefaultSpread_t + \epsilon_t \quad (8)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $WRET_t$ is the daily return of the Wilshire 5000 Total Market Index. $WARET_t$ is the 5-day absolute return of the index. $WVARRET_t$ is the 5-day return variance of the index. $ShortRate_t$ is the daily difference in Federal Fund Rate. $TermSpread_t$ is the daily change in the difference between the yield on a constant maturity 10-year T-bond and the Federal Fund Rate. $DefaultSpread_t$ is the daily change in the difference between Moody's Baa or Better Corporate Bond Index yield and the yield on a constant maturity 10-year T-bond. α is the constant, and ϵ_t is the error term.

In equation (8), the first three variables represent the stock market movement and volatility, whereas the last three variables represent interest rates' evolution. Table 3.5 shows the regression results of equation (8). We reveal that both *MAFE* and *Ln(MSFE)* from the prediction model positively correlate with market volatility measured by $WARET_t$ and negatively link to market return, $WRET_t$. The effect of market volatility proxied by $WVARRET_t$ on *MAFE* and *Ln(MSFE)* is mixed. Furthermore, we find a positive relation between forecast errors from the VAR model and $DefaultSpread_t$. In general, these results indicate that the VAR model's accuracy reduces when the market is down and volatile and when the market default risk is increasing. These results highlight the limitation of this VAR model as its accuracy deteriorates when it is most needed.

Table 3.5. Effect of Macro-Variables on Forecast Errors
Notes: This table presents the results of the following model:

$$FOR\_ERROR_t = \alpha + \beta_1 WRET_t + \beta_2 WARET_t + \beta_3 WVARRET_t + \beta_4 ShorRate_t + \beta_5 TermSpread_t + \beta_6 DefaultSpread_t + \epsilon_t \quad (8)$$

where FOR_ERROR_t is the 1-step ahead forecast error of the VAR model to predict ETF bid-ask spread. The forecast error can be the daily mean absolute forecast error (*MAFE*) or the logarithm of the daily mean squared forecast error (*Ln(MSFE)*) of the model. $WRET_t$ is the daily return of the Wilshire 5000 Total Market Index. $WARET_t$ is the 5-day absolute return of the index. $WVARRET_t$ is the 5-day return variance of the index. $ShortRate_t$ is the daily difference in Federal Fund Rate; $TermSpread_t$ is the daily change in the difference between the yield on a constant maturity 10-year T-bond and the Federal Fund Rate; $DefaultSpread_t$ is the daily change in the difference between the yield on Moody's Baa or Better Corporate Bond Index and the yield on a constant maturity 10-year T-bond; α is the constant and ϵ_t is the error term. ***, **, and * represent statistical significance at the 1%, 5% and 10%, respectively.

Independent	Using MAFE			Using Ln(MSFE)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
WRET	-0.589^{***}	-0.577^{***}	-0.589^{***}	-7.120^{***}	-6.89^{***}	-7.115^{***}
	(-2.55)	(-2.51)	(-2.55)	(-17.32)	(-19.28)	(-17.31)
WARET	5.859^{***}	4.886^{***}	5.861^{***}	109.92^{***}	84.25^{***}	109.81^{***}
	(6.68)	(5.50)	(6.68)	(70.4)	(61.11)	(70.33)
WVARRET	0.752^{***}	0.788^{***}	0.753^{***}	-339.8^{***}	-29.34^{***}	-339.2^{***}
	(2.93)	(3.07)	(2.94)	(-7.45)	(-74)	(-7.43)
ShortRate	-0.08	-0.062	-0.079	-0.775^{***}	-0.427^{***}	-0.774^{***}
	(-1.08)	(-0.84)	(-1.08)	(-5.88)	(-3.73)	(-5.87)
TermSpread	-0.006	-0.002	-0.006	0.115	0.173^{**}	0.116
	(-0.15)	(-0.05)	(-0.15)	(1.55)	(2.67)	(1.55)
DefaultSpread	0.218^{***}	0.212^{***}	0.218^{***}	0.148^{***}	1.456^{***}	1.664^{***}
	(2.62)	(2.57)		(11.11)	(11.33)	(11.12)
			(2.62)			
Intercept	0.118^{***}			-14.73^{***}		
	(30.17)			(212)		
ETF fixed effect	No	Yes	No	No	Yes	No
Year fixed effect	No	No	Yes	No	No	Yes
Number of Observations	810,087	810,087	810,087	810,087	810,087	810,087
Adj. R^2	0.004	0.004	0.004	0.0189	0.0259	0.0190

3.4.3. Economic benefit of the model

This section examines the economic benefit of using the VAR model's bid-ask spread predictions to schedule trade compared to other trading schedules. We consider the perspectives of both large and retail ETF traders.

3.4.3.1. For large ETF trader

We test if a trading schedule derived from the model can produce economic benefits for an ETF investor with a large order to trade. Scheduling trades for large orders have significant implications for both informed (Easley and O'Hara, 1987) and liquidity traders (Admati and Pfleiderer, 1988). The informed trader wants to uncover the private information from the order size to maximize gains from trade. The liquidity trader also likes to hide his demand for liquidity to avoid front running and minimize trade's implicit cost (Keim and Madhavan, 1997). Regardless of the traders' reason to trade, large traders have a strong incentive to split their orders to reduce implicit trading costs (Alam and Tkatch, 2009). As evidence, Chordia and Subrahmanyam (2011) find that while the value-weighted average monthly share turnover of stocks on NYSE increased from 5% to 26% from 1993 to 2008, the average daily number of transactions increased ninety-fold during the same period. This fact implies that splitting orders have been a norm to reduce transaction costs for many traders.

Consistent with the above literature about large traders' trading behavior, this study assumes that the investor using the VAR model to schedule his trade is a large trader who splits his order over the trading day. The trader has 13 30-minute trading horizons[15] during the trading day, and in each trading horizon, he will trade one-thirteenth of his volume scheduled for the day. His objective is to purchase ETF units at any time during each trading horizon where the bid-ask spread is lowest. For instance, at 9:30 am on 03 Jan 2011, this investor wants to trade ETF *i*. The VAR model has five forecasts of bid-ask spread from 9:35 am (1-step ahead forecast) to 9:55 am (5-step ahead forecast). If the current spread at 9:30 am is lower than all *h*-step ahead forecasts, this investor will trade immediately. Otherwise, this investor will

[15] These 13 trade horizons are equivalent to 13 30-minute time intervals during the trading day.

choose the point in time where the bid-ask spread forecast is the lowest to trade. For example, if the 2-step ahead forecast at 9:40 am is the lowest, then an investor will trade at 9:40 am and then incur the actual bid-ask spread at that time. The next trade horizon will start at 10:00 am.

We compare the executed bid-ask spread using this VAR trading schedule to that of the following trading schedules:

- *Naïve trading schedule*: In this trading schedule, trades occur immediately at the beginning of each 30-minute trade horizon. In the above example, the bid-ask spread around 9:30 am is the bid-ask spread executed by naïve investors. Taylor (2002) used this trading schedule as his benchmark trading schedule.
- *M.A. trading schedule*: In this trading schedule, the trader uses bid-ask spread forecasts from the moving average model to schedule his trades. The trading rules are the same as the VAR trading schedule except that we replace the bid-ask spread forecasts from the VAR model with the bid-ask spread forecasts from the moving average model.
- *Random trading schedule*: In this trading schedule, we assume that the trader can split his order more frequently than 13 times each trading day. He can trade an equal amount of his demand for each bid-ask spread quote of the trading day, and he will incur the average bid-ask spread for each trade horizon and each trading day.

This study also assumes that there are no commission costs, and opportunity costs are the same for different strategies. Based on these assumptions, reducing execution costs is determined by minimizing spread payment.

Table 3.6 presents the average executed bid-ask spread under different trading schedules for each time interval during the day and its corresponding economic benefit. The last row shows the pooled average of the executed bid-ask spread and economic benefit variables. We calculate the economic benefit in Table 3.6 as the spread discount between the executed bid-ask spread using the VAR model and that under three reference trading schedules: *Naïve trading schedule*, *M.A. trading schedule,* and *Random trading schedule.* The formula to compute the economic benefit is:

$$ECO\_BEN_{Var,j,t}=(AVE\_BAS_{j,t} -AVE\_ BAS_{Var,t})/AVE\_BAS_{j,t} \quad (9)$$

where $ECO\_BEN_{VAR,j,t}$ is the economic benefit of the VAR trading schedule compared to trading schedule j in interval t. $Ave\_BAS_{j,t}$ is the average executed bid-ask spread of ETFs using trading schedule j in interval t. $Ave\_BAS_{VAR,t}$ is the average executed bid-ask spread of ETFs using the VAR trading schedule in interval t.

From Table 3.6, we find that the daily average executed bid-ask spread using the VAR model to schedule trades is 36.16 basis points, which is lower than that from other models. Using the VAR model could save traders about 7.4% compared to using a naïve trading schedule in terms of economic benefit. The VAR trading schedule's average spread is 8.29% lower than that of the M.A. trading schedule. Compared to the average bid-ask spread of a random investor, the spread saving is as high as 30.81%. In summary, these results indicate that scheduling trades based on the VAR model's bid-ask spread forecasts can help large traders save their spread costs while allowing them to split their orders over time.

Table 3.6. Economic Benefit of VAR Model to Trade ETFs

Notes: This table presents the executed bid-ask spread under different trading schedules for a large ETF trader. These trading schedules are:

- *VAR trading schedule*: The trader has 13 30-minute trading horizons during the trading day, and in each trading horizon, he will trade one-thirteenth of his volume scheduled for the day. His objective is to purchase ETF units at any time during each trading horizon where the bid-ask spread is lowest. For instance, at 9:30 am on 03 Jan 2011, this investor wants to trade ETF *i*. Based on the VAR-model, he has 5 forecasts of bid-ask spread at 9:35am (1-step ahead forecast) to 9:55 am (5-step ahead forecast). If the current spread around 9:30 am is lower than all *h*-step ahead forecasts, this investor will trade immediately. Otherwise, this investor will choose the point in time where the bid-ask spread forecast is lowest to trade. For example, the 2-step ahead forecast at 9:40 am is lowest then the investor will trade at 9:40 am and then incur the actual bid-ask spread at that time. The next trade horizon will start at 10:00 am.
- *Naïve trading schedule*: In this trading schedule, trades take place immediately during the 30-minute trade horizon. In the above example, the bid-ask spread at around 9:30 am is the bid-ask spread executed by naïve investors. This trading schedule was used by Taylor (2002) as his benchmark trading schedule.
- *M.A. trading schedule*: In this trading schedule, the trader uses bid-ask spread forecasts from the moving average model to schedule his trades. The trading rules are the same as the VAR trading schedule except that the bid-ask spread forecasts from the VAR model are replaced by bid-ask spread forecasts from the moving average model.
- *Random trading schedule*: In this trading schedule, we assume that the trader can split his order more frequently than 13 times each trading day. He can trade an equal amount of his order for each bid-ask spread quote of the trading day and he will incur the average bid-ask spread for each trade horizon and each trading day.

The economic benefit in Table 3.6 is calculated as the spread discount between the executed bid-ask spread using the VAR model and that under three reference trading schedules: *Naïve trading schedule*, *M.A. trading schedule*, and *Random trading schedule.* The formula to compute the economic benefit is:

$$ECO\_BEN_{VAR,j,t}=(AVE\_BAS_{j,t} - AVE\_BAS_{Var,t})/AVE\_BAS_{j,t} \quad (9)$$

where $ECO\_BEN_{VAR,j,t}$ is the economic benefit of the VAR trading schedule compared to trading schedule *j* in interval *t*. $AVE\_BAS_{j,t}$ is the average executed bid-ask spread of ETFs using trading schedule *j* in interval *t*. $AVE\_BAS_{VAR,t}$ is the average executed bid-ask spread of ETFs using the VAR trading schedule in interval *t*.

Time	Average Bid-Ask Spread (in basis points)				Economic Benefit		
Interval	AVE_BAS_{VAR}	AVE_BAS_{Naive}	AVE_BAS_{MA}	AVE_BAS_{Random}	$ECO\_BEN_{VAR,Naive}$	$ECO\_BEN_{VAR,MA}$	$ECO\_BEN_{VAR,Random}$
1	38.56	40.27	40.68	65.52	4.25%	5.21%	41.15%
2	32.35	34.19	36.01	46.71	5.38%	10.16%	30.74%
3	31.24	32.79	34.60	41.92	4.73%	9.71%	25.48%
4	30.54	32.02	33.82	41.08	4.62%	9.70%	25.66%
5	30.21	31.46	33.48	41.03	3.97%	9.77%	26.37%
6	30.15	31.44	33.32	41.74	4.10%	9.51%	27.77%
7	29.78	31.05	33.44	40.18	4.09%	10.94%	25.88%
8	30.09	32.29	33.61	39.72	6.81%	10.47%	24.24%
9	29.99	31.19	33.46	40.24	3.85%	10.37%	25.47%
10	29.62	30.90	33.12	40.65	4.14%	10.57%	27.13%
11	29.00	31.29	35.01	39.99	7.32%	17.17%	27.48%
12	132.4	147.4	88.97	140.1	10.18%	-48.81%	5.50%
13	91.69	94.18	107.82	56.01	2.64%	14.96%	-63.70%
Mean	36.16	39.05	39.43	52.27	7.40%	8.29%	30.81%

We report the intraday economic benefit patterns using the VAR model's trading schedule compared to other trading schedules in Table 3.6. We find that traders can enjoy economic benefits from the VAR model most of the time during the trading day. For instance, the VAR trading schedule's economic benefit compared to the naïve trading schedule, $ECO\_Ben_{VAR,\ Naive}$, is lowest at the open and the close of the trading day. After the opening, the economic benefit rises and then becomes stable. The highest economic benefits happen during the last two intervals before the market closure.

3.4.3.2. For retail ETF trader

This section compares the average bid-ask spread under different trading schedules mentioned in section 4.3.1 to a simple trading rule of trading at the close. Trading at the close has many hidden costs for traders with a large order to execute or traders possessing private information. For traders with a large order to execute, there is implementation shortfall risk as they might be able to execute only a fraction of their orders around the close. For traders possessing private information, delaying trade until the close can reduce their information advantages. Furthermore, Cushing and Madhavan (2001) also point to the risk of significant price movement at the close caused by institutional demand. Despite these disadvantages, Bacidore, Polidore, Xu, and Yang (2012) find that the closing time is generally the most actively traded period of the day. Some traders choose to trade around the close either because they choose the closing price as their benchmarks (e.g., index funds) or because the improved liquidity around this time attracts them. As a result, we expect that scheduling trade at the close would be enticing from the perspective of a retail ETF trader who executes only small orders and does not trade based on private information.

In table 3.7, we present the comparison of the average bid-ask spread under different trading schedules and the average closing bid-ask spread of ETFs. We compute the average numbers using different averaging methodologies, including pooled, cross-sectional, and time-series averages. The pooled average closing bid-ask spread of ETFs ($AVE\_BAS_{Closing}$) is only 19.69 basis points, representing a discount of 45% compared to the average bid-ask spread of the VAR trading schedule[16]. When trading at the close, the retail ETF trader described above can save up significantly his spread cost compared to splitting trades over the trading day using different trading schedules.

Table 3.7. Average Bid-Ask Spreads of Different Trading Schedules

Notes: This table presents the daily average executed bid-ask spread under different trading schedules. The average bid-ask spread of each model is calculated using three following calculation methodologies: *1/Pooled average*: Averaging all executed bid-ask spread of each trading rules for all ETFs in the sample; *2/ Cross-sectional average*: First daily executed bid-ask spread is calculated for each ETFs as the average of all executed bid-ask spreads during the day (for trading rules using VAR, MA and Taylor's benchmark). For trading at the close strategy, a daily executed bid-ask spread is the closing bid-ask spread. For random trading strategy, a daily executed bid-ask spread is the average of all bid-ask spreads during the day. Daily executed bid-ask spreads are averaged for each ETF over the sample period then the results are averaged cross-sectionally across all ETFs to have the average bid-ask spread for each trading rule and *3/ Time-series average*: Daily executed bid-ask spread for each ETF is calculated the same as the cross-sectional average. The daily executed bid-ask spreads for ETFs in the sample are averaged for each day and then the results are averaged across the research period to have the average bid-ask spread for each trading rule.

Variables	Pooled Average	Cross-sectional Average	Time-series Average
AVE_BAS_{VAR}	36.16	37.67	38.90
AVE_BAS_{Naive}	39.05	41.07	42.42
AVE_BAS_{MA}	39.43	40.04	40.33
AVE_BAS_{Random}	52.77	50.32	53.99
AVE_BAS_{Close}	19.69	15.82	21.95

3.4.4. Economic benefit and spread volatility

In Taylor's (2002) paper, he finds that the VAR model can save trading stocks' transaction costs on the London Stock Exchange by about 34% compared to a naïve trading schedule. We find that this spread saving for ETFs is 7.40% on average for a large ETF trader. As we calculate the spread saving of the VAR trading schedule using the gap between ETF

[16] Our regression of the intraday pattern of ETF liquidity in Appendix B.2 shows that the time-weighted bid-ask spread tends to be low during the last 15-minute interval.

spreads throughout the day, it could depend on the level of spread volatility of ETF. In the extreme case that the spread is flat for the whole day, the economic benefit will be zero regardless of forecasts from the VAR model. As a result, we expect the VAR model to yield better cost savings when the spread is more volatile. In other words, we conjecture that there is more room to save spread costs by timing trades during the day when spread volatility is high.

In Table 3.8, we break down the daily economic benefit derived from the VAR model compared to the naïve trading schedule ($Eco\_Ben_{Var,\ Naïve,t}$) into different spread volatility ranks and ETF sectors. In Panel A, ETFs are cross-sectionally classified into quintiles of spread volatility daily. We use two daily spread volatility measures: the daily percentage spread range (*RANSPR)* and the daily coefficient of variation of the spread (*COVARSPR*). We compute the percentage spread range by dividing the daily spread range by the daily mean bid-ask spread. The spread range is the maximum spread minus the minimum spread. We calculate the spread coefficient of variation as the ratio of the standard deviation of the intraday bid-ask spread to the daily mean bid-ask spread. Our descriptive statistics of economic benefit in Panel A show that economic benefit is higher for more spread volatile ETFs. In Panel B, we classify ETFs into various sectors. We observe higher economic benefits for ETFs like Commodities or Equity and lower economic benefit for ETFs such as Tax Preferred or Fixed Income.

Table 3.8. Breakdown of Economic Benefit

Notes: This table presents the economic benefit of the VAR trading schedule compared to the naïve trading schedule ($ECO\_BEN_{VAR,Naïve}$) of different ETF groups classified by their spread volatilities (Panel A) and sectors (Panel B). In Panel A, we use two measures of daily spread volatility, which are the daily percentage spread range (*RANSPR)* and the daily coefficient of variation of the spread (*COVARSPR*). *RANSPR* is computed by dividing the daily spread range to the daily mean bid-ask spread. Spread range is the maximum spread minus the minimum spread. *COVARSPR* is calculated by dividing the standard deviation of the intraday bid-ask spread to the daily mean bid-ask spread.

Panel A. By Spread Volatility

ETF Spread Volatility Ranking	$ECO\_BEN_{VAR,Naive}$	
	Ranked by RANSPR	Ranked by COVARSPR
1 (*Lowest spread volatility*)	4.47%	4.76%
2	5.29%	5.29%
3	5.91%	5.77%
4	6.59%	6.41%
5 (*Highest spread volatility*)	7.17%	7.21%

Panel B. By ETF Sector

ETF Sector	Number of ETFs	$ECO\_BEN_{VAR,Naive}$
Allocation	30	4.67%
Alternative	271	6.46%
Commodities	25	9.47%
Convertibles	2	9.64%
Equity	796	6.01%
Fixed Income	199	5.03%
Tax Preferred	27	3.88%

To formally test our expectation, we regress the following equation:

$$ECO\_BEN_{Var,Naïve,t} = \alpha + \beta_1 SPR\_VOL_{E,t} + \beta_2 RETVAR_{E,t} + \beta_3 LDVOL_{E,t} + \beta_4 LogMV_{E,t} + \beta_5 WRET_t + \beta_6 WARET_t + \beta_7 WVARRET_t + \beta_8 ShorRate_t + \beta_9 TermSpread_t + \beta_{10} DefaultSpread_t + \epsilon_t \quad (10)$$

where $ECO\_BEN_{VAR,Naïve,t}$ is the daily economic benefit of the VAR trading schedule compared to the naïve trading schedule for each ETF. $SPR\_VOL_{E,t}$ is the daily volatility of ETF spread measured by either the daily percentage spread range ($RANSPR_{E,t}$) or the daily coefficient of variation ($COVARSPR_{E,t}$). $RETVAR_{E,t}$ is the 5-day return variance of ETF. $LDVOL_{E,t}$ is the logarithm of the daily dollar trading volume of ETF. $LogMV_{E,t}$ is the logarithm of the daily market value of ETF. $WRET_t$ is the daily return of the Wilshire 5000 Total Market Index. $WARET_t$ is the 5-day absolute return of the index. $WVARRET_t$ is the 5-day return variance of the index. $ShortRate_t$ is the daily difference in Federal Fund Rate; $TermSpread_t$ is the daily change in the difference between the yield on a constant maturity 10-year T-bond and the Federal Fund Rate; $DefaultSpread_t$ is the daily change in the difference between the yield on Moody's Baa or Better Corporate Bond Index and the yield on a constant maturity 10-year T-bond; α is the constant and ϵ_t is the error term.

Table 3.9 reports the regression results of the above equation. We find that spread volatility positively correlates with the economic benefit calculated from the VAR model. This positive relation is also robust for both proxies of spread volatility, *RANSPR*, and *COVARSPR*. These regression results are consistent with our expectation that the more volatile the spread is, the more spread savings opportunity from the VAR model. Besides spread volatility, we also reveal other ETF characteristics that could affect the model's economic benefit. We find evidence that the economic benefit is higher for ETF with higher return volatility (*RETVAR*), higher trading activity (*LDVOL*), and lower size (*LogMV*).

Table 3.9. Economic Benefit and Spread Volatility

Notes: This table presents the regression results of the following model:

$$ECO\_BEN_{VAR,Naïve,E,t} = \alpha + \beta_1 SPR\_VOL_{E,t} + \beta_2 RETVAR_{E,t} + \beta_3 LDVOL_{E,t} + \beta_4 LogMV_{E,t} + \beta_5 WRET_t + \beta_6 WARET_t + \beta_7 WVARRET_t + \beta_8 ShorRate_t + \beta_9 TermSpread_t + \beta_{10} DefaultSpread_t + \epsilon_t \quad (10)$$

where $ECO\_BEN_{VAR,Naïve,E,t}$ is the daily economic benefit of the VAR trading schedule compared to naïve trading schedule for each ETF. $SPR\_VOL_{E,t}$ is the daily volatility of ETF spread measured by either daily percentage spread range ($RANSPR_{E,t}$) or the daily coefficient of variation of the spread ($COVARSPR_{E,t}$). The percentage spread range is computed by dividing the daily spread range to the daily mean bid-ask spread. Spread range is the maximum spread minus the minimum spread. The coefficient of variation is calculated by dividing the standard deviation of the intraday bid-ask spread to the daily mean bid-ask spread. $RETVAR_{E,t}$ is the 5-day return variance of ETF; $LDVOL_{E,t}$ is the logarithm of daily dollar trading volume of ETF; $LogMV_{E,t}$ is the daily logarithm of the market value of ETF. $WRET_t$ is the daily return of the Wilshire 5000 Total Market Index. $WARET_t$ is the 5-day absolute return of the index. $WVARRET_t$ is the 5-day return variance of the index. $ShortRate_t$ is the daily difference in Federal Fund Rate; $TermSpread_t$ is the daily change in the difference between the yield on a constant maturity 10-year T-bond and the Federal Fund Rate; $DefaultSpread_t$ is the daily change in the difference between the yield on Moody's Baa or Better Corporate Bond Index and the yield on a constant maturity 10-year T-bond; α is the constant and ϵ_t is the error term. ***, **, and * represent statistical significance at the 1%, 5% and 10%, respectively.

Independent Variables	Using Spread Range as Proxy for Spread Volatility			Using Coefficient of Variation as Proxy for Spread Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
RANSPR	0.014***	0.017***	0.014***			
	(29.44)	(31.89)	(29.45)			
COVARSPR				1.022***	1.014***	1.01***
				(70.70)	(68.41)	(69.84)
RETVAR	39.83***	34.05***	39.81***	45.85***	0.445***	0.644***
	(18.96)	(10.52)	(18.95)	(21.89)	(9.29)	(24.91)
LDVOL	0.010***	0.089***	0.047***	0.049***	0.098***	0.059***
	(4.69)	(7.67)	(4.70)	(4.97)	(8.46)	(6.00)
LogMV	-0.485***	-0.803***	-0.485***	-0.589***	-0.844***	-0.571***
	(-26.86)	(-28.37)	(-26.85)	(-32.56)	(-29.85)	(-31.53)
WRET	-15.01***	-14.67***	-15.01***	-16.78***	-16.71***	-16.62***
	(-4.54)	(-4.47)	(-4.53)	(-5.08)	(-5.11)	(-5.04)
WARET	124.99***	111.3***	124.9***	124.87***	114.7***	99.39***
	(9.83)	(8.53)	(9.82)	(9.85)	(8.47)	(7.76)
WVARRET	-865.28**	-747.9**	-866.2**	-867.3**	-335.8	-144.2
	(-2.35)	(-2.03)	(-2.35)	(-2.36)	(-0.92)	(-0.39)
ShortRate	0.876	1.268	0.877	1.689	1.880*	1.67
	(0.86)	(1.2)	(0.82)	(1.59)	(1.78)	(1.57)
TermSpread	0.489	0.607	0.49	0.634	0.712	0.616
	(0.41)	(1.02)	(0.82)	(1.06)	(1.20)	(1.03)
DefaultSpread	4.657***	4.402***	4.669***	4.367***	4.274***	4.431***
	(3.91)	(3.73)	(3.92)	(3.67)	(3.63)	(3.73)

Intercept	6.58***			6.634***		
	(40.65)			(41.15)		
ETF Fixed Effect	No	Yes	No	No	Yes	No
Fixed-Year Effect	No	No	Yes	No	No	Yes
Number of Observation	829,507	829,507	829,507	829,507	829,507	829,507
Adjusted R^2	0.0038	0.0242	0.0038	0.0089	0.0285	0.0091

3.5. Conclusion

Despite the growing importance of trading ETFs, there is little evidence of the predictability of ETF bid-ask spread. Our paper examines the degree to which investors can minimize ETF trading costs using bid-ask spread predictions from a VAR model. Using a large sample of 1,350 US ETFs between January 2011 and December 2017, we find that this VAR model can produce better bid-ask spread forecasts than a moving average model in the short term. Furthermore, we document that the optimal trading schedule for ETFs to minimize bid-ask spread cost depends on traders' type. For a large ETF trader who is more likely to split his order to hide his trading motives, the VAR trading schedule is superior to other trading schedules. For a retail ETF trader who does not possess private information and trades a small amount of ETF shares, trading at the close is the best in terms of spread saving as ETF bid-ask spreads tend to be lowest around the closing time.

Finally, we reveal that the VAR trading schedule's cost-saving compared to the naïve trading schedule is widely diverse across ETF sectors. While the benefit of timing trades is as low as 3.88% for Tax Preferred ETFs, it is nearly 9.5% for Commodities ETFs. One possible explanation for the difference in expected cost savings across ETFs and between ETF and stock could be the spread of volatility. When security is more volatile in the spread, it will have more room to minimize spread costs by timing trades. We find a positive correlation between spread volatility and spread saving, which lends support to our conjecture. Furthermore, as an ETF is a diversified portfolio where idiosyncratic risk is low and diversified, ETF has less volatility than stock. The ETFs might offer less room to minimize transaction costs than individual stocks.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Son Pham
Name/title of Primary Supervisor:	Professor Nuttawat Visaltanachoti
Name of Research Output and full reference:	
Predicting ETF liquidity	
In which Chapter is the Manuscript /Published work:	Chapter Three
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	70 percent
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
Son collected and cleaned the data. He conducted the empirical results from the data and wrote the paper. During the weekly meetings, the supervisors answered to Son's questions and gave their comments about the empirical results. This paper	
For manuscripts intended for publication please indicate target journal:	
Financial Analysts Journal	
Candidate's Signature:	Pham Duy Son Digitally signed by Pham Duy Son Date: 2021.06.21 17:26:02 +12'00'
Date:	
Primary Supervisor's Signature:	Visaltanachoti, Nuttawat Digitally signed by Visaltanachoti, Nuttawat Date: 2021.06.22 11:53:59 +12'00'
Date:	

(This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis)

CHAPTER FOUR: ESSAY THREE

This chapter presents the third essay which investigates the liquidity spillover between an ETF and its underlying portfolio. A brief overview of the key findings is presented in Section 4.1. Section 4.2 reviews related literature. Section 4.3 presents the data and the methodologies used in the essay. Section 4.4 reports the core results and related discussion. Section 4.5 concludes this chapter. Appendices to this chapter and the essay's reference list are provided at the end of thesis.

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 spillover increases during the market crisis, economic downturn, and positively relates 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

4.1. Introduction

Exchange-traded funds (ETFs) are one of the most successful financial innovations of recent decades. As of December 2017, there was $3.4 trillion in US ETF assets under management, and a total number of 1,832 ETFs with 85.6% of US ETFs were index trackers[17]. The ETF market's rapid growth globally has been coincided with one of the longest bull markets in history and is yet to experience a prolonged period of volatility. The ETF market scale and its 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 is the first attempt to document the magnitude and determinants of liquidity spillover between an ETF and its underlying portfolio. It contributes to addressing

[17] SIFMA Insights: US ETF Market Structure Primer. September 2018. Retrieved from: https://www.sifma.org/wp-content/uploads/2018/09/SIFMA-Insights-US-ETF-Primer.pdf

a growing concern from both investors and regulators about the simultaneous dry ups of liquidity in financial markets, as shown in the recent market “flash crashes”.

ETF sponsors widely promote ETF as having superior liquidity, 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”[18]. 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)[19]. However, Ben-David, Franzoni, and Moussawi (2018) find that a shock to ETF liquidity could propagate to underlying liquidity or vice versa and leads 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 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, the plummeting and illiquid securities[20]. Thus, both ETF and underlying liquidity dry up simultaneously, leading to fire sales in both markets (e.g., Su, 2018).

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[18] 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

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

[20] 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.

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. We find that the ETF liquidity and its underlying liquidity Granger cause each other. Following Diebold and Yilmaz (2012), we compute the pairwise spillover and liquidity spillover index between the ETF and its underlying portfolio. 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 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. We reveal that liquidity spillover has many common market-level determinants as 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 period 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 limits of arbitrage and is 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 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 change in the 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; Choridia, Roll, and Subrahmanyam, 2002). We examine the effect of funding costs on liquidity spillover using various funding costs and find their results are different. An increase in the short-term rate reduces the liquidity spillover, whereas a rise in default spread increases the liquidity spillover. Furthermore, using a regulatory experiment on short-sale constraints, our difference-in-difference analysis provides evidence 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 as it affects asset pricing and market stability (e.g., Pastor and Stambaugh, 2003). The dry-up of liquidity combined with an increased liquidity co-movement between different asset classes or other geographic markets is of great interest to market regulators, practitioners, and researchers. The propagation of liquidity shocks from one asset class to another asset class receives less attention (Cespa and Foucault, 2014) compared to the liquidity co-movement within an asset class. (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 spillover and by the empirical outcomes 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 comprehensive analysis of market-level determinants of liquidity spillover.

Second, our paper contributes to the literature of 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 in 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[21].

Finally, our research directly addresses the growing concern among practitioners, researchers, and market regulators about the "liquidity illusion" risk exposed by the ETF market. Our present work is the first to investigate this risk's magnitude and evolution over time, to the best of our knowledge. We find a significant liquidity spillover between the ETF and its underlying portfolio, especially during period of economic slowdown. 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 4.2 discusses related literature and formulate the hypotheses. In section 4.3, we describe the data and methodologies used. In section 4.4, we present the empirical results and discussion. Concluding remarks are provided in section 4.5.

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[21] Our findings give a reason for the usage of short sale ban during the time of 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 18th, 2020 to May 18th, 2020.

4.2. Literature review and development of hypotheses

4.2.1. 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 theory of "wealth effect" which attributes liquidity spillover across assets to shocks to financial intermediaries' risk aversion. During a market crisis, loss in one market increases their 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 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 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 lead 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 as it is 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 spillover from ETF to the underlying portfolio.

There is some 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 that there is 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 that 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 that from the ETF to the underlying portfolio.

4.2.2. 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.

4.2.2.1. 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 heightened spillover effect during the market crisis or economic recession. For instance, Diebold and Yilmaz (2009) find that volatility spillover between equity markets are 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 when the market volatility rises, liquidity suppliers risk losing the collateral values and reduce 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 be a proxy of the market maker's risk tolerance. According to De Long, Shleifer, Summers, and Waldman (1990), the optimism or pessimism sentiments in the market caused by noise traders. These sentiments generate transitory divergences between price and the 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. 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 that a bearish investor sentiment reading 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 time of economic slowdown. Furthermore, it is positively correlated with the market decline and volatility and negatively correlated with the investor sentiment index's bullishness.

4.2.2.2. 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 limits of arbitrage and is 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 or creation/redemption activity of ETF correlates with the liquidity spillover between them. 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 short-sale restrictions are associated with violations of put-call parity in the options market. Fung and Draper (1999), Gay and Jung (1999) find that short-sale limitations are the source of mispricing in the futures market as it limits index arbitrage activity. We expect that by affecting arbitrage activity between ETFs and component stocks, short sale constraints could affect liquidity spillover between them.

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.

4.3. Data and liquidity spillover estimation

4.3.1. *Data*

Our research uses the DIAMONDS ETF and its component stocks as our study's scope, with the research period from April 1st, 2002 to December 31st, 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 October 2020, the DIAMONDS ETF has assets under management of USD 22.816 billion, making it one of the fifty largest ETFs listed in US markets. Daily data of 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 macro-economic 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[22]. Data of put-call ratio and the CBOE Volatility Index (VIX) are from the database of Chicago Board Options Exchange[23] (CBOE). Data on investor sentiment index, the high-low ratio, comes from the website barchart.com. We gather data on the monthly United States Purchasing Managers Index (PMI) on the Datastream for economic activity.

Our paper also uses a regulatory experiment to investigate the impact of stock price informativeness on the liquidity spillover. This regulatory experiment is the Regulation SHO pilot program, designated to remove short-sale constraints for randomly selected stocks listed

[22] https://fred.stlouisfed.org/
[23] http://www.cboe.com/data/historical-options-data/volume-put-call-ratios

in U.S. markets from May 2nd, 2005 to August 6th, 2007. The list of pilot securities is collected online via the Securities and Exchange Commission (SEC)[24].

4.3.2. *Methodology*

4.3.2.1. *Liquidity proxies*

Our paper uses two proxies to measure the liquidity of the ETF and its underlying stocks. These proxies are daily quoted bid-ask spread and daily Amihud illiquidity ratio. The daily quoted bid-ask spread (QSPR) is:

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

where $ASK_{i,d}$, and $BID_{i,d}$ are quoted ask and bid prices of the ETF or stock *i* on day *d*. As defined by Amihud (2002), the daily Amihud illiquidity ratio (*Amihud*) of the ETF or a stock is calculated as:

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

where $R_{i,d}$, and $V_{i,d}$ are the return and dollar volume on day *d* of stock *i* or the ETF.

4.3.2.2. *Diebold and Yilmaz's (2012) spillover index*

[24] https://www.sec.gov/spotlight/shopilot.htm.

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

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

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. (1) becomes:

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

where the NxN coefficient matrices A_i follow the recursion

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

with A_0 being an NxN 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), 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,…, 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 *j*th 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 known as 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 that 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. 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, 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:

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

4.3.2.3. *Liquidity spillover index*

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 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, or the Amihud illiquidity ratio described in Eqs. (1) and (2). We use daily high and low prices to compute Parkison's (1980)[25] 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. We apply the adjustment for seasonality and deterministic variations following Gallant, Rossi, and Tauchen's (1992). The number of lags, *k*, in Eqs. (12) and (13) is 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. It is the average value of pairwise spillovers between the ETF liquidity and the underlying liquidity calculated using the 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;

[25] 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).

4.3.2.4. *Main regression equation*

To investigate the determinants of liquidity spillover between the ETF and its underlying liquidity, we first construct a non-overlapped time series of *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[26]. Then we regress the following equation:

$$WLSI_t = \alpha + Controls_t + Interests_t + \varepsilon_t \quad (16)$$

where $WLSI_t$ is the *Weekly Liquidity Spillover Index* between the ETF and its underlying portfolio using either the bid-ask spread or Amihud illiquidity ratio. $Controls_t$ is a set of control variables including ETF_CAP_t and ETF_VOLUME_t, with ETF_CAP_t being the logarithm of the weekly average market capitalization of the ETF measured in USD million and ETF_VOLUME_t being the logarithm of weekly average trading volume of the ETF measured in thousands of shares. $Interests_t$ is a set of variables of interest.

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

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

using a 205-day window and the 5-day lagged value of the rolling pairwise spillover between 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 *WDLSIs*, one from the ETF to its underlying portfolio ($WDLSI_{ETF>Underlying}$) and one from the underlying portfolio to the ETF ($WDLSI_{Underlying>ETF}$). Determinants of *WDLSI* are examined through the following regression:

$$WDLSI_t = \alpha + Controls_t + Interests_t + \varepsilon_t \qquad (17)$$

where $WDLSI_t$ is a *Weekly Directional Liquidity Spillover Index* between the ETF and its underlying portfolio using either the bid-ask spread or Amihud illiquidity ratio. $Controls_t$ and $Interests_t$ in Eq. (17) are the same as in Eq. (16).

4.4. Empirical results

4.4.1. Magnitude and direction of liquidity spillover

4.4.1.1. Descriptive statistics and diagnostic tests

In Table 4.1 Panel A, we report the descriptive statistics of variables in Eqs. (12) and (13) and their diagnostic tests. The mean value of the ETF bid-ask spread ($QSPR_E$) 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 C.1, 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 20 and we can reject the null of no autocorrelation at the 1% level for all variables in the VAR model. In addition, we use the Jarque-Bera statistic to test the normality of the VAR model's variables. The Jarque-Bera statistics in Table 4.1 Panel A confirm the non-normality behaviour of the variables.

As the VAR model requires that its variables should be stationary, we conduct two tests for stationarity of the variables and report the results in Table 4.1 Panel B. The first is the Augmented Dickey Fuller test (ADF) and the second is Phillips-Perron test (PP). From the results of both tests, we can reject the null hypothesis that there is unit root in the time series. In other words, these variables are stationary and suitable as inputs for the VAR model.

In Table 4.1 Panel C, we present the correlation matrix of variables in the VAR model. As the ETF tracks its underlying portfolio, there is 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 illiquidity is 0.742.

Table 4.1. Descriptive Statistics, Diagnostic Tests, and Correlation Matrix of Variables in VAR Model

Notes: 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 $Amihud_{U,t}$). In Panel A, Q(20) denotes the Ljung-Box Statistics (up to 20 days), and JB-Test denotes the Jarque and Bera (1980) statistic. In Panel B, ADF Test refers to the Augmented Dickey Fuller (ADF) test, and PP test refers to Phillips-Perron test. Individual intercept and time trend are included in the test regressions. 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.

Panel A. Descriptive statistics

Variable	Obs.	Mean	Median	Standard Deviation	Min	Max	Kurtosis	Skewness	Q(20)	JB-Test
$QSPR_E$	3689	0.013	0.01	0.014	0.005	0.303	189.68	8.16	6978***	4642***
$Amihud_E$	3689	0.0007	0.0006	0.0008	0	0.013	3.91	1.56	1663***	3223***
VOL_E	3689	0.062	0.058	0.021	0.025	0.209	5.59	1.99	1949***	6047***
RET_E	3689	0.036	0.074	1.126	7.520	13.56	6.12	0.08	59.05***	4806***
$QSPR_U$	3689	0.054	0.030	0.071	0.010	0.642	12.47	1.88	3702***	2172***
$Amihud_U$	3689	0.0024	0.0018	0.0017	0.00043	0.025	5.65	1.90	7893***	5949***
VOL_U	3689	0.011	0.0094	0.006	0.004	0.087	7.12	2.29	2169***	9176***
RET_U	3689	0.044	0.061	1.100	-7.495	10.51	5.34	0.06	62.90***	3651***

Panel B. Results of stationarity tests

	$QSPR_E$	$Amihud_E$	VOL_E	RET_E	$QSPR_U$	$Amihud_U$	VOL_U	RET_U
ADF Test	-37.80***	-49.03***	-12.58***	-59.81***	-16.54***	-39.44***	-12.56***	-60.44***
PP Test	-47.18***	-55.20***	-11.83***	-60.48***	-16.44***	-50.27***	-11.68***	-61.29***

Panel C. Correlation matrix

	$QSPR_E$	$Amihud_E$	VOL_E	RET_E	$QSPR_U$	$Amihud_U$	VOL_U	RET_U
$QSPR_E$	1.00							
$Amihud_E$	0.286	1.00						
VOL_E	0.319	0.297	1.00					
RET_E	0.056	0.079	0.043	1.00				
$QSPR_U$	0.680	0.363	0.417	-0.062	1.00			
$Amihud_U$	0.505	0.742	0.418	0.023	0.674	1.00		
VOL_U	0.383	0.272	0.913	0.046	0.489	0.449	1.00	
RET_U	-0.065	0.083	0.046	0.986	-0.049	0.031	0.055	1.00

4.4.1.2. Granger causality test

We use Granger causality to discern a lead-lag relationship between the ETF and its underlying liquidity. Table 4.2 reports the results of 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 4.2 show strong evidence of 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 254.26 and 55.58, respectively. They are both statistically significant ($p\text{-}value$ < 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 also significant, with 45.61 and 48.44, respectively.

Table 4.2. Granger Causality Tests

Notes: 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 of 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.

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

	$QSPR_E$	VOL_E	RET_E	$QSPR_U$	VOL_U	RET_U
$QSPR_E$		18.75 (0.0046)	22.91 (0.0008)	55.58 (0.0001)	9.79 (0.134)	27.36 (0.0001)
VOL_E	90.31 (0.0001)		6.73 (0.346)	31.02 (0.0001)	25.47 (0.0003)	7.04 (0.317)
RET_E	30.88 (0.0001)	343.7 (0.0001)		34.98 (0.0001)	289.5 (0.0001)	2.08 (0.913)
$QSPR_U$	254.26 (0.0001)	38.43 (0.0001)	16.09 (0.0133)		50.94 (0.0001)	19.32 (0.0037)
VOL_U	88.09 (0.0001)	48.68 (0.0001)	17.30 (0.008)	22.54 (0.001)		15.71 (0.015)
RET_U	29.26 (0.0001)	345.40 (0.0001)	5.74 (0.453)	36.12 (0.0001)	282.12 (0.0001)	

Panel B. Using Amihud illiquidity as liquidity measure

	$Amihud_E$	VOL_E	RET_E	$Amihud_U$	VOL_U	RET_U
$Amihud_E$		49.19 (0.0001)	8.39 (0.211)	48.44 (0.001)	37.50 (0.0001)	7.29 (0.29)
VOL_E	101.08 (0.0001)		6.73 (0.346)	103.07 (0.0001)	25.47 (0.0003)	7.04 (0.317)
RET_E	79.83 (0.0001)	343.7 (0.0001)		159.99 (0.0001)	289.5 (0.0001)	2.08 (0.913)
$Amihud_U$	45.61 (0.0001)	38.27 (0.0001)	14.06 (0.029)		36.07 (0.0001)	12.86 (0.045)
VOL_U	88.85 (0.0001)	48.68 (0.0001)	17.30 (0.008)	80.97 (0.0001)		15.71 (0.015)
RET_U	76.00 (0.001)	345.40 (0.0001)	5.74 (0.453)	153.22 (0.0001)	282.12 (0.0001)	

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 C.2. 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. The results of Test 1 indicate that ETF liquidity Granger causes stock liquidity for 37 out of 43 component stocks using the bid-ask spread as liquidity proxy. This ratio is 32/43 when using Amihud as liquidity proxy. The results of Test 2 also confirm the bi-directional relationship between ETF and underlying liquidity. They show that the bid-ask spread of 39 stocks Granger causes that of ETF while the Amihud ratio of 32 stocks Granger causes the ETF's Amihud illiquidity. Overall, the results are consistent with those in Table 4.2 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 C.3. 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, which is the modified Amihud illiquidity suggested by Florackis, Gregoriou, and Kostakis (2011) for our VAR model in Eqs. (12) and (13). We find that the modified Amihud illiquidity ratio is strongly related to the Amihud illiquidity. The coefficient of correlation 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 C.4. These results confirm those in Table 4.2.

4.4.1.3. 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 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 4.3. We construct Panels A and B of Table 4.3 using bid-ask spread and Amihud illiquidity ratio as liquidity proxies, respectively.

In Table 4.3, 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. *From the others* 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. *To the others* 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 the others* and *From the others* for each variable in the table. *Total 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, shocks to the ETF bid-ask spread, $QSPR_E$ in the second column, explains only 4.9% of the variation in forecast error of the underlying bid-ask spread, $QSPR_U$ in the fourth row.

Table 4.3. Direction and Magnitude of Spillover

Notes: This table reports the direction and the magnitude of spillover between stock and ETF market liquidity and trading variables. The spillover index is computed as proposed by Diebold and Yilmaz (2012) based on the following VAR model:

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

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

where X and Y are vectors that represent liquidity, return, and volatility of the DIAMONDS ETF and those of 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 $Amihud_{U,t}$). A diagonal value represents the spillover of own variable, off-diagonal elements for each column represent pairwise spillover to other variables, and off-diagonal elements for each row represent pairwise spilllover received from other variables. *Total Spillover Index* is ratio of total contribution to the others divided by total contribution including own. *Liquidity Spillover Index* is the average of pairwise spillovers between the ETF and its underlying liquidity.

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

	$QSPR_E$	VOL_E	RET_E	$QSPR_U$	VOL_U	RET_U	From the 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 the 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 the 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 the 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 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%).

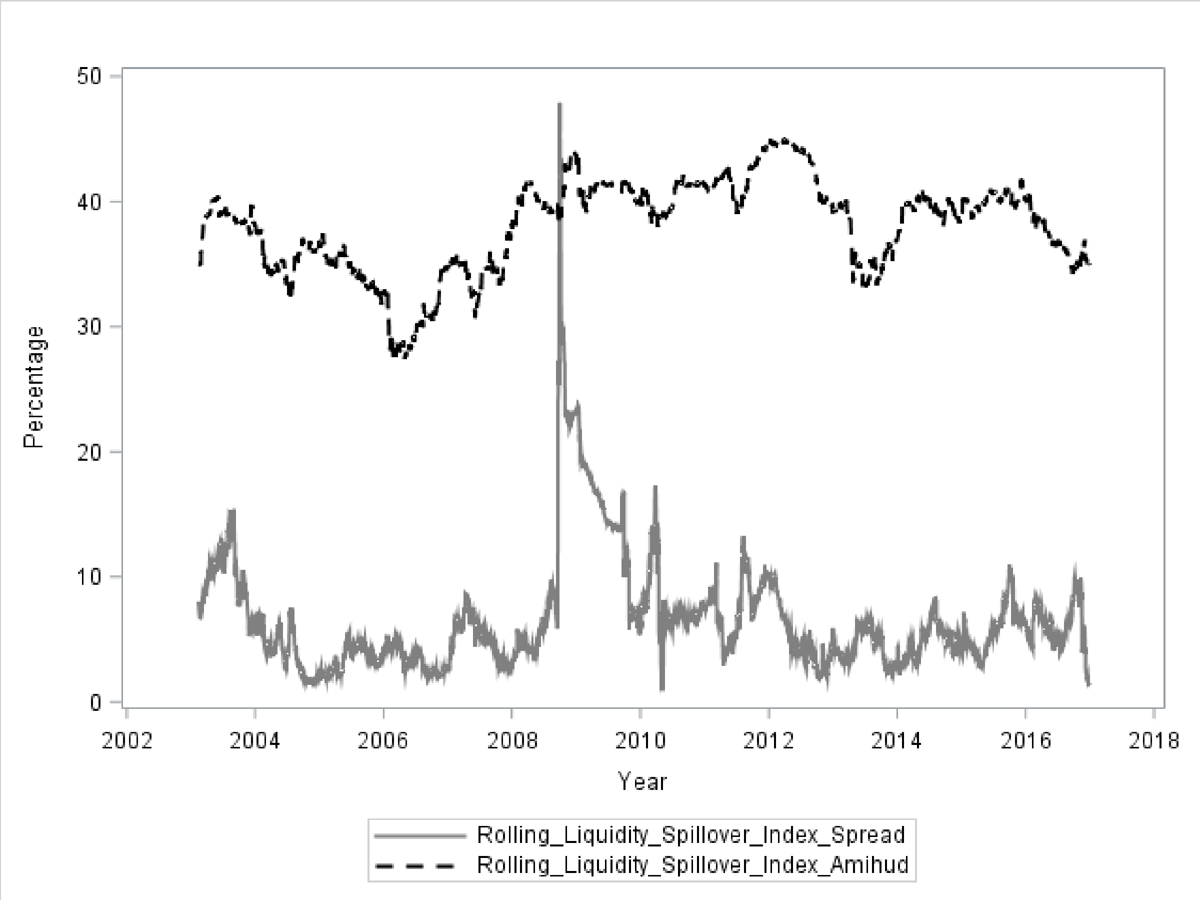
In Table 4.3 Panel B, the pairwise spillovers from the underlying Amihud to the ETF Amihud and vice versa are 33.7% and 28.49%, respectively. The *Liquidity Spillover Index* between them is 31.12%, significantly higher than the bid-ask spread spillover. Overall, the results in Table 3 convey three important messages regarding Hypothesis 1 proposed in Section 2.1. First, there exists the liquidity spillover between the DIAMONDS ETF and its underlying portfolio. Second, among other variables in the model except its own 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, which is consistent with our expectation. The above remarks are similar for both models using either bid-ask spread or Amihud illiquidity ratio as a liquidity proxy.

4.4.2. 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 Hypothesis 2 and 3. In Figure 4.1, we plot 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 compared to the *LSI* using the Amihud illiquidity ratio, the *LSI* using the bid-ask spread is more volatile. It has increased to as high as nearly 50% during the GFC period (2017-2019). The *WLSI* time series using spread and Amihud illiquidity ratio are in Figure 4.2.

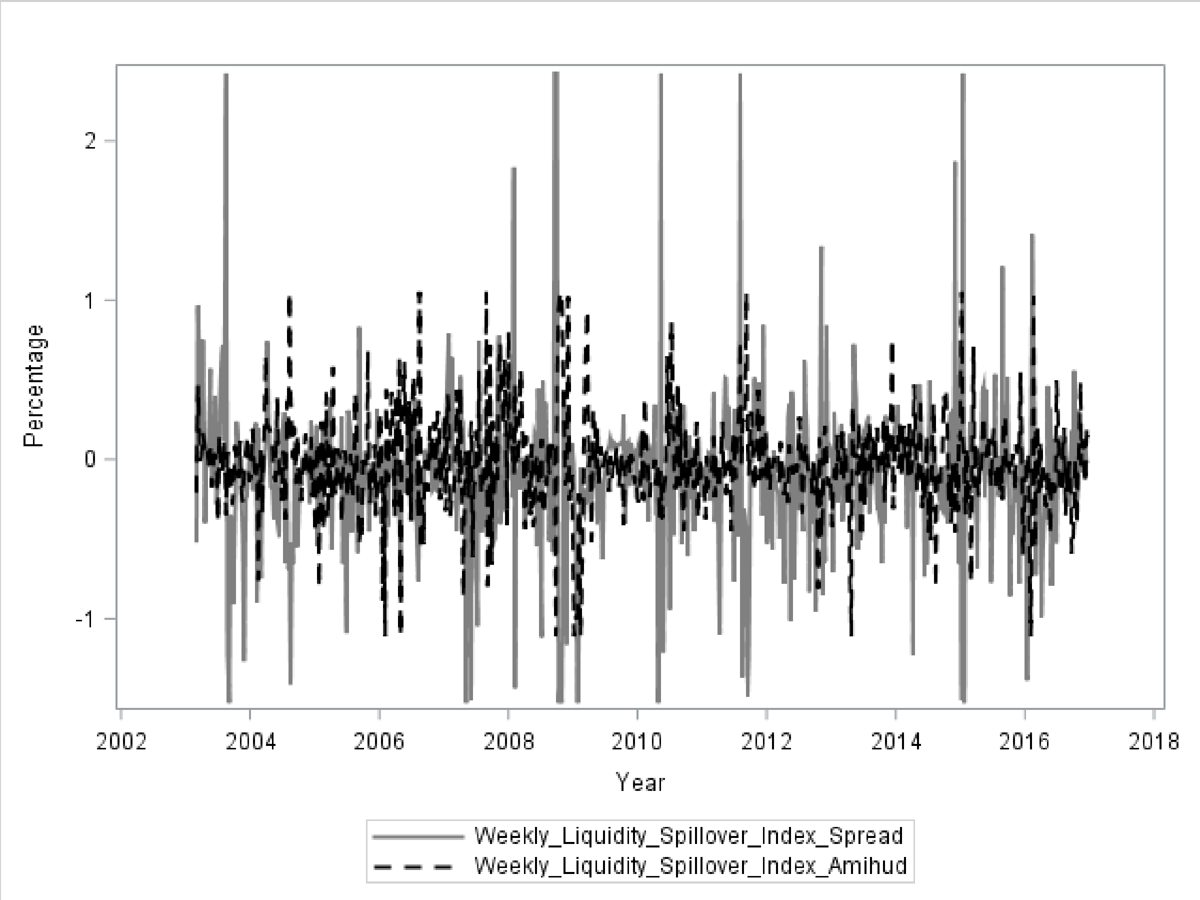
Figure 4.1. Rolling Liquidity Spillover Index 2002-2016

Notes: 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 total spillover index using the quoted bid-ask spread as a liquidity proxy and the broken line is the rolling total spillover index using the Amihud illiquidity ratio as a liquidity proxy.



As in Hypothesis 2, we expect that liquidity spillover between the DIAMONDS ETF and its underlying portfolio will increase during economic recession or financial crisis. These economic stages are usually characterized by a declining stock market, lower economic activity, and greater stock volatility. All these factors contribute to increasing 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.

Figure 4.2. Weekly Liquidity Spillover Index 2002-2016
Notes: 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.



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[27] 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_t has a value of 0 if the PMI is below or equal 50 and 1 if the PMI is higher than 50. To proxy for the market conditions, we use MKT_RET_t, which is the weekly

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

market return of the S&P 500 index, and MKT_STD_t, which is the weekly market volatility measured as the standard deviation of market returns for five consecutive trading days.

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_t) 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 down versus investors betting on the stock price 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 market mood is bullish. In addition to the PCR, we use another market sentiment index: the high-low index (HLR_t) of the S&P 500. This index compares the number of component stocks of the S&P 500 that 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 is a signal of bullish market sentiment and vice versa.

The regression results of Eqs. (16) and (17) using the above variables of interest are presented in Table 4.4. We report results using the bid-ask spread and Amihud as liquidity proxies in Panel A and Panel B, respectively. We use the *WLSI* as the dependent variable for model specifications (1), (2), and (3); the $WDLSI_{ETF>Underlying}$ as the dependent variable for model specifications (4), (5), and (6); the $WDLSI_{Underlying>ETF}$ 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_t 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 a period of economic slowdown 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 ($WDLSI_{ETF>Underlying}$), as shown in model specifications (4), (5), and (6) in Panel A, and the liquidity spillover from the underlying portfolio to the ETF ($WDLSI_{Underlying>ETF}$), 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 ($WDLSI_{ETF>Underlying}$) and that from the underlying portfolio to the ETF ($WDLSI_{Underlying>ETF}$) 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 ($WDLSI_{ETF>Underlying}$) is muted as shown in model specifications (4), (5), and (6) whereas the liquidity spillover from the underlying portfolio to the ETF ($WDLSI_{Underlying>ETF}$) is positively correlated with market volatility as in model specifications (7) and (9).

Table 4.4. Liquidity Spillover and Market Conditions

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

$WLSI_t = \alpha + Controls_t + Interests_t + \varepsilon_t$ (16)

$WDLSI_t = \alpha + Controls_t + Interests_t + \varepsilon_t$ (17)

where $WLSI_t$ and $WDLSI_t$ 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. ETF_CAP_t and ETF_VOLUME_t are control variables ($Controls_t$). ETF_CAP_t is the logarithm of weekly average market capitalization of the ETF measured in million dollars. ETF_VOLUME_t is the logarithm of weekly average trading volume of the ETF measured in thousands of shares. PMI_D_t, MKT_RET_t, MKT_STD_t, PCR_t, and HLR_t are variables of interest ($Interest_t$). PMI_D_t is a dummy variable for economic expansion, which equals 1 if the PMI is higher than 50 and zero otherwise. MKT_RET_t is the weekly market return measured as the weekly return of the S&P500 index. MKT_STD_t is the weekly market volatility measured as the standard deviation of market return for one week. PCR_t is the weekly average of the daily put-call ratio of stocks on New York Stock Exchange. HLR_t 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.

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

	WLSI			$WDLSI_{ETF>Underlying}$			$WDLSI_{Underlying>ETF}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF_CAP	0.13	0.12	0.13	0.17	0.19	0.17	0.01	-0.01	0.02
	(1.36)	(1.31)	(1.38)	(1.24)	(1.39)	(1.23)	(0.06)	(-0.12)	(0.13)
ETF_VOLUME	-0.04	-0.04	-0.04	0.001	0.001	0.001	-0.06	-0.08	-0.06
	(-0.71)	(-0.77)	(-0.70)	(0.01)	(0.12)	(0.01)	(-0.91)	(-1.06)	(0.88)
PMI_D	-0.13**	-0.14**	-0.13**	-0.09	-0.07	-0.09	-0.07	-0.10	-0.07
	(-2.08)	(-2.24)	(-2.09)	(-1.04)	(-0.84)	(-1.03)	(-0.96)	(-1.35)	(-1.00)
MKT_RET	-0.76	-0.52	-0.75	1.64	1.02	1.64	-0.84	0.05	-0.81
	(-0.77)	(-0.56)	(-0.76)	(1.13)	(0.75)	(1.12)	(-0.67)	(0.04)	(-0.65)
MKT_STD	10.48**	9.87**	10.50**	-6.33	-4.69	-6.34	10.44**	8.20*	10.51**
	(2.56)	(2.48)	(2.57)	(-1.06)	(-0.80)	(-1.06)	(2.04)	(1.65)	(2.06)
PCR	-0.15		-0.21	0.51		0.55	-0.59		-0.77*
	(-0.50)		(-0.66)	(1.18)		(1.19)	(-1.58)		(-1.94)
HLR		-0.002	-0.004		-0.002	0.002		-0.001	-0.001
		(-0.36)	(-0.57)		(-0.18)	(0.24)		(-0.69)	(-1.31)
Intercept	-2.39	-2.30	-2.41	-4.37	-4.64	-4.35	1.06	1.39	0.99
	(-0.89)	(-0.86)	(-0.90)	(-1.11)	(-1.18)	(-1.11)	(0.32)	(0.41)	(0.30)
Observations	667	667	667	667	667	667	667	667	667
R-squared	0.021	0.021	0.022	0.013	0.011	0.013	0.011	0.007	0.014

Panel B. Using Amihud illiquidity as liquidity measure

	WLSI			$WDLSI_{ETF>Underlying}$			$WDLSI_{Underlying>ETF}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF_CAP	-0.08	-0.06	-0.07	-0.09	-0.08	-0.08	-0.06	-0.05	-0.06
	(-1.29)	(-1.06)	(-1.20)	(-1.24)	(-1.10)	(-1.17)	(-0.99)	(-0.71)	(-0.90)

ETF_VOLUME	-0.07*	-0.06*	-0.07*	-0.09**	-0.09**	-0.09**	-0.03	-0.02	-0.03
	(-1.81)	(-1.68)	(-1.78)	(-2.22)	(-2.15)	(-2.20)	(-0.75)	(-0.58)	(-0.72)
PMI_D	-0.16***	-0.16***	-0.16***	-0.14***	-0.14***	-0.15***	-0.17***	-0.16***	-0.17***
	(-4.02)	(-3.94)	(-4.08)	(-3.28)	(-3.27)	(-3.33)	(-3.87)	(-3.73)	(-3.93)
MKT_RET	0.88	0.64	0.90	0.68	0.54	0.70	0.82	0.48	0.84
	(1.37)	(1.07)	(1.40)	(0.94)	(0.80)	(0.97)	(1.19)	(0.76)	(1.23)
MKT_STD	10.53***	11.27***	10.57***	13.00***	13.47***	13.05***	7.42***	8.42***	7.47***
	(3.97)	(4.38)	(4.00)	(4.38)	(4.68)	(4.40)	(2.63)	(3.08)	(2.66)
PCR	0.36*		0.23	0.27		0.14	0.46**		0.32
	(1.90)		(1.13)	(1.24)		(0.62)	(2.24)		(1.46)
HLR		-0.001**	-0.001*		-0.001*	-0.001*		-0.001**	-0.001*
		(-2.45)	(-1.92)		(-1.92)	(-1.59)		(-2.54)	(-1.88)
Intercept	2.56	2.39	2.51	3.14*	3.03*	3.09*	1.58	1.36	1.53
	(1.47)	(1.38)	(1.45)	(1.62)	(1.56)	(1.59)	(0.86)	(0.74)	(0.83)
Observations	667	667	667	667	667	667	667	667	667
R-squared	0.055	0.059	0.061	0.049	0.053	0.054	0.044	0.046	0.049

We find that liquidity spillover using the bid-ask spread as liquidity proxy is not affected by market sentiment indexes. However, when the Amihud illiquidity ratio is used, the results show that the market sentiment index measured by HLR_t affects liquidity spillover in tandem with our expectations. Specifically, the coefficient of HLR_t in columns (2) and (3) is significantly negative, indicating that when the market is bearish (i.e., HLR is low) the liquidity spillover between the ETF and its underlying portfolio tends to be higher.

In summary, we find intriguing results about the asymmetrical effect of market conditions on the directional liquidity 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 the underlying spread. The market return does not influence the directional liquidity spillover between the ETF and its underlying portfolio as its coefficient is nonsignificant for all model specifications. Overall, our results indicate that the liquidity shock from underlying stocks to ETF is greater than vice versa, and it is more affected by the market-level determinants.

4.4.3. ETF arbitrage and liquidity spillover

4.4.3.1. Impact of creation/redemption and 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, from ETF trading data, we cannot measure the arbitrage activity. 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 the absolute flow as the first proxy of ETF arbitrage activity in our paper. Consistent with Clifford, Furkerson, and Jordan (2014), Broman and Shum (2018), we compute the absolute fund flows, $ABS\_FUND\_FLOW_t$, as below:

$$ABS\_FUND\_FLOW_t = |SHR_t - SHR_{t-1}| * NAV_t / AUM_{t-1} \tag{18}$$

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 $t-1$. As we hypothesize that liquidity spillover increases when ETF arbitrage activity intensifies, the coefficient of $ABS\_FUND\_FLOW_t$ is expected to be positive and statistically significant.

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_t). 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 absolute fund flows ($ABS\_FUND\_FLOW_t$) and the pricing error ((PRC_ERR_t) of the ETF. $ABS\_FUND\_FLOW_t$ is the average of daily percentage absolute change in fund inflow or outflow of ETF in one week and PRC_ERR_t is the average pricing error of ETF for one week.

Table 4.5. Liquidity Spillover and Creation/Redemption Activity

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

$$WLSI_t = \alpha + Controls_t + Interests_t + \varepsilon_t \quad (16)$$

$$WDLSI_t = \alpha + Controls_t + Interests_t + \varepsilon_t \quad (17)$$

where $WLSI_t$ and $WDLSI_t$ 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. ETF_CAP_t and ETF_VOLUME_t are control variables ($Controls_t$). ETF_CAP_t is the logarithm of the weekly average market capitalization of the ETF measured in million dollars. ETF_VOLUME_t is the logarithm of the weekly average trading volume of the ETF measured in thousands of shares. $ABS\_FUND\_FLOW_t$ *and* PRC_ERR_t are variables of interest ($Interest_t$). $ABS\_FUND\_FLOW_t$ is the average of the daily percentage absolute change in fund inflow or outflow of the ETF in one week. PRC_ERR_t 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.

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

	WLSI			$WDLSI_{ETF>Underlying}$			$WDLSI_{Underlying>ETF}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF_CAP	0.14	0.25**	0.24**	0.13	0.13	0.13	-0.0001	0.04	0.04
	(1.54)	(2.68)	(2.63)	(1.00)	(0.93)	(0.90)	(-0.01)	(0.36)	(0.32)
ETF_VOLUME	0.01	-0.04	-0.06	-0.08	-0.07	-0.08	-0.03	-0.04	-0.05
	(0.30)	(-1.02)	(-1.34)	(-1.40)	(-1.05)	(-1.20)	(-0.60)	(-0.72)	(-0.98)
ABS_FUND_FLOW	2.45**		2.03*	1.42		1.45	2.27*		2.14*
	(2.15)		(1.80)	(0.86)		(0.87)	(1.60)		(1.50)
PRC_ERR		1.87***	1.79***		-0.05	-0.11		0.71	0.062
		(3.92)	(3.73)		(-0.07)	(-0.15)		(1.18)	(1.03)
Intercept	-3.51	-5.31*	-4.97*	-1.86	-2.01	-1.77	0.36	-0.49	-0.15
	(-1.47)	(-2.21)	(-2.07)	(-0.53)	(-0.57)	(-0.50)	(0.12)	(-0.16)	(-0.05)
Observations	667	667	667	667	667	667	667	667	667
R-squared	0.012	0.029	0.035	0.01	0.01	0.01	0.005	0.002	0.006

Panel B. Using Amihud illiquidity as liquidity measure

	WLSI			$WDLSI_{ETF>Underlying}$			$WDLSI_{Underlying>ETF}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF_CAP	-0.05	-0.05	-0.06	-0.04	-0.03	-0.04	-0.05	-0.06	-0.07
	(-0.91)	(-0.86)	(-0.94)	(-0.78)	(-0.50)	(-0.53)	(-0.72)	(-0.92)	(-1.02)
ETF_VOLUME	0.01	0.02	0.01	0.03	0.02	0.02	-0.003	0.033	0.01
	(0.18)	(0.76)	(0.27)	(0.94)	(0.73)	(0.54)	(-0.09)	(1.02)	(0.40)
ABS_FUND_FLOW	1.90**		1.92**	0.79		0.34	2.66***		2.75***
	(2.54)		(2.55)	(0.99)		(0.92)	(3.19)		(3.28)
PRC_ERR		0.001	-0.08		0.27	0.24		-0.28	-0.39
		(0.00)	(-0.24)		(0.79)	(0.70)		(-0.77)	(-1.09)
Intercept	1.12	0.87	1.18	0.68	0.36	0.48	1.10	0.97	1.42

	(0.71)	(0.55)	(0.74)	(0.41)	(0.22)	(0.29)	(0.63)	(0.54)	(0.80)
Observations	667	667	667	667	667	667	667	667	667
R-squared	0.015	0.004	0.015	0.007	0.007	0.008	0.02	0.004	0.022

The regression results of Eqs. (16) and (17) with the above variables of interest are in Table 4.5. We find that absolute fund flow, $ABS\_FUND\_FLOW_t$ 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 $ABS\_FUND\_FLOW_t$. The ETF pricing error results, PRC_ERR_t are less impressive as it only positively relates to liquidity spillover calculated using the bid-ask spread. The regression results also show asymmetrical effects of arbitrage activity on directional liquidity spillover. In both panels, we find that arbitrage activity only positively relates to the liquidity spillover from the underlying portfolio to its ETF ($WDLSI_{Underlying>ETF}$) as shown in columns (7) and (9). Overall, our results in this part are consistent with Hypothesis 3 and in line with the proposition of Ben-David, Franzoni, and Moussawi (2018) about the role of arbitrage in transmitting shocks between ETFs and underlying portfolios.

4.4.3.2. 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[28] of funding costs on the intensity of liquidity spillover between the DIAMONDS ETF and its underlying portfolio. These proxies are $SHORTRATE_t$ as the weekly change in the Federal Funds Rate; $TERMSPREAD_t$ as the weekly change in the difference between the yield on a constant maturity 10-year Treasury bond and the Federal Funds Rate; $DEFAULTSPREAD_t$ as

[28] 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.

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_t 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 be different. 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 be an indicator of lower risk aversion in the marketplace as it implies a higher employment rate and better economic activity. Similarly, an increase in $TERMSPREAD_t$ indicates that the yield curve is steepening, and the economy is expected to be stronger[29]. Consequently, an increase in $TERMSPREAD_t$ can be associated with lower risk aversion among ETF dealers. From the above discussion, we expect that the effect of $SHORTRATE_t$ and $TERMSPREAD_t$ on liquidity spillover is significantly negative.

In contrast, we expect an increase in the credit risk in the economy ($DEFAULTSPREAD_t$) 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 $DEFAULTSPREAD_t$ has opposing effects on the liquidity spillover between the ETF and its underlying portfolio. A higher credit risk implies more risk 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

[29] 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.

spillover. Consequently, we expect that the net effect of $DEFAULTSPREAD_t$ 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_t will have a positive impact on 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 4.6 reports the regression results of Eqs. (16) and (17). We use *WLSI*, $WDLSI_{ETF>Underlying}$, and $WDLSI_{Underlying>ETF}$ 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, $DEFAULTSPREAD_t$ 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. 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.

Table 4.6. Liquidity Spillover and Funding Costs

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

$WLSI_t = \alpha + Controls_t + Interests_t + \varepsilon_t$ (16)

$WDLSI_t = \alpha + Controls_t + Interests_t + \varepsilon_t$ (17)

where $WLSI_t$ and $WDLSI_t$ 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. ETF_CAP_t and ETF_VOLUME_t are control variables ($Controls_t$). ETF_CAP_t is the logarithm of the weekly average market capitalization of the ETF measured in million dollars. ETF_VOLUME_t is the logarithm of the weekly average trading volume of the ETF measured in thousands of shares. $SHORTRATE_t$, $TERMSPREAD_t$, $DEFAULTSPREAD_t$, *and* YLD_STD_t are variables of interest ($Interest_t$). $SHORTRATE_t$ is the weekly change in the Federal Fund Rate. $TERMSPREAD_t$ is the weekly change in the difference between the yield on a constant maturity 10-year Treasury bond and the Federal Funds rate. $DEFAULTSPREAD_t$ 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_t 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.

Panel A. Using WLSI

	Bid-ask spread					Amihud				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF_CAP	0.11	0.14	0.11	0.19	0.13	-0.06	-0.05	-0.07	-0.03	-0.06
	(1.24)	(1.56)	(1.21)	(2.08)	(1.41)	(-1.00)	(-0.93)	(-1.27)	(-0.55)	(-0.98)
ETF_VOLUME	0.013	0.04	0.04	-0.02	-0.05	0.02	0.02	0.001	-0.002	-0.02
	(0.32)	(0.94)	(0.10)	(-0.56)	(-1.21)	(0.073)	(0.75)	(0.04)	(-0.09)	(-0.78)
SHORTRATE	-0.065***				-0.33	0.002				-0.21
	(-3.17)				(-1.23)	(0.01)				(-1.14)
TERMSPREAD		0.25**			0.22		-0.19**			-0.24**
		(2.04)			(1.31)		(-2.35)			(-2.08)
DEFAULTSPREAD			0.79***		0.83***			0.52***		0.31*
			(3.11)		(2.99)			(3.07)		(1.69)
YTD_STD				3.05***	2.29***				1.29**	1.14**
				(3.74)	(2.75)				(2.39)	(2.05)
Intercept	-2.9	-3.94	-2.69	-4.13*	-2.32	1.08	0.97	1.72	0.75	1.69
	(-1.19)	(-1.63)	(-1.11)	(-1.74)	(-0.95)	(0.67)	(0.61)	(1.08)	(0.48)	(1.04)
Observations	667	667	667	667	667	667	667	667	667	667
R-squared	0.021	0.012	0.021	0.028	0.054	0.004	0.014	0.020	0.014	0.034

Panel B. Using $WDLSI_{ETF>Underlying}$

	Bid-ask spread					Amihud				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF_CAP	0.11	0.13	0.11	0.16	0.11	-0.06	-0.05	-0.07	-0.02	-0.05
	(0.80)	(1.02)	(0.85)	(1.18)	(0.79)	(-0.83)	(-0.73)	(-0.97)	(-0.35)	(-0.67)
ETF_VOLUME	-0.09	-0.07	-0.09	-0.09	-0.12*	0.02	0.02	0.005	-0.07	-0.02
	(-1.61)	(-1.19)	(-1.51)	(-1.61)	(-1.91)	(0.55)	(0.67)	(0.18)	(-0.23)	(-0.73)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SHORTRATE	-0.71**				-0.38	-0.08				-0.25
	(-2.35)				(-0.94)	(-0.56)				(-1.25)
TERMSPREAD		0.35*			0.28		-0.12			-0.21
		(1.93)			(1.12)		(-1.36)			(-1.63)
DEFAULTSPREAD			0.46		0.59			0.39**		0.18
			(1.23)		(1.45)			(2.06)		(0.90)
YTD_STD				1.53	0.82				1.51**	1.36**
				(1.28)	(0.66)				(2.49)	(2.19)
Intercept	-1.09	-2.18	-1.33	-2.19	-0.71	1.04	0.81	1.41	0.61	1.39
	(-0.31)	(-0.62)	(-0.37)	(-0.63)	(-0.2)	(0.58)	(0.46)	(0.79)	(0.34)	(0.76)
Observations	667	667	667	667	667	667	667	667	667	667
R-squared	0.017	0.014	0.009	0.01	0.022	0.004	0.006	0.01	0.013	0.023

Panel C. Using $WDLSI_{Underlying>ETF}$

	Bid-ask spread					Amihud				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF_CAP	-0.05	-0.01	-0.001	0.02	-0.04	-0.05	-0.05	-0.07	-0.04	-0.06
	(-0.42)	(-0.07)	(-0.01)	(0.15)	(-0.37)	(-0.80)	(-0.82)	(-1.15)	(-0.58)	(-0.95)
ETF_VOLUME	-0.04	-0.01	-0.01	-0.03	-0.5	0.03	0.03	0.01	0.02	-0.001
	(-0.87)	(-0.16)	(-0.24)	(-0.56)	(-0.92)	(1.25)	(1.10)	(0.38)	(0.65)	(-0.03)
SHORTRATE	-0.96***				-0.68**	0.14				-0.11
	(-3.78)				(-2.00)	(0.94)				(-0.60)
TERMSPREAD		0.48***			0.25		-0.26***			-0.26**
		(3.13)			(1.18)		(-3.04)			(-2.14)
DEFAULTSPREAD			0.09		0.26			0.56***		0.35*
			(0.30)		(0.74)			(3.15)		(1.87)
YTD_STD				1.04	0.36				0.77	0.66
				(1.01)	(0.34)				(1.33)	(1.13)
Intercept	1.69	0.21	0.13	-0.04	1.67	0.61	0.70	1.48	0.5	1.40
	(0.56)	(0.07)	(0.04)	(-0.01)	(0.54)	(0.35)	(0.42)	(0.88)	(0.3)	(0.81)
Observations	667	667	667	667	667	667	667	667	667	667
R-squared	0.024	0.017	0.0002	0.002	0.027	0.007	0.021	0.022	0.01	0.034

In Panel A, the coefficient of yield volatility, YTD_STD_t is also significantly positive for all model specifications, including it as a regressor. 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, $TERMSPREAD_t$ 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, $SHORRATE_t$ reduces liquidity spillover, in line with our expectation.

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 ($WDLSI_{ETF>Underlying}$) calculated using bid-ask spread. However, the yield volatility (YTD_STD_t) is positively correlated with the $WDLSI_{ETF>Underlying}$ computed using Amihud illiquidity. In Panel C, we find an increase in Fed Fund Rate ($SHORRATE_t$) has a negative impact on liquidity spillover from the ETF spread to its underlying spread as in columns (1) and (5). The effect of $TERMSPREAD_t$ is mixed whereas $DEFAULTSPREAD_t$ only positively affects the $WDLSI_{Underlying>ETF}$ calculated using Amihud illiquidity.

4.4.3.3. 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. In this part, we investigate 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. In the following paragraphs, we will describe the regulation change, design the difference-in-difference (DiD) analysis, and report the DiD results.

The SEC announced the 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 within each exchange, and every third one 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. On July 6, 2007, this program ended when the SEC eliminated short-selling price tests for all exchange-listed stocks. As ETF arbitrage is an important channel to fuel liquidity spillover between ETF and underlying stocks, we expect that the Regulation SHO pilot program will bolster pilot stocks' arbitrage activity in the ETF and increase their liquidity spillover with the ETF.

Among 43 constituent stocks of the DIAMONDS ETF from 2002 to 2016, only six stocks[30] 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

[30] These stocks' tickers are DIS, HD, INTC, JNJ, KO, and WMT.

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 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 the 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:

$$WLSI_{i,t} = \alpha + \beta_1 PILOT_{i,t}*DURING_{i,t} + \beta_2 PILOT_i*POST_{i,t} + \beta_3 PILOT_{i,t} + \beta_4 DURING_{i,t} + \beta_4 POST_{i,t} + Controls_{i,t} + \varepsilon_i \quad (19)$$

where $WLSI_{i,t}$ 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* equals one if stock *i* is in the pilot group and zero otherwise. *DURING* equals one if the weekly liquidity spillover index's end date is between Q3/2005 to Q2/2007 and zero otherwise. *POST* equals one if the weekly liquidity spillover index's end date is between Q3/2007 to Q2/2009 and zero otherwise. The *Controls* are 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[31]. We expect that the coefficient β_1 is significantly positive, which implies that relaxing the short-sale constraints positively impacts the liquidity spillover of pilot component stocks with ETF.

Table 4.7. Liquidity Spillover and Short Sale Constraints

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

$$WLSI_{i,t}= \alpha + \beta_1 PILOT_{i,t}*DURING_{i,t}+ \beta_2 PILOT_{i,t}*POST_{i,t} + \beta_3 PILOT_{i,t} + \beta_4 DURING_{i,t} + \beta_5 POST_i + \beta_6 SIZE_{i,t} + \beta_7 STD_{i,t} + \beta_8 TURNOVER_{i,t} + \beta_9 WEIGHT_{i,t} + \varepsilon_t \quad (19)$$

where $WLSI_{i,t}$ 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. $PILOT_{i,t}$ equals 1 if stock *i* is in the pilot group, and zero otherwise. $DURING_{i,t}$ equals 1 if the end date of the *WLSI* is between Q3/2005 to Q2/2007. $POST_{i,t}$ equals 1 if the end date of the weekly *WLSI* is between Q3/2007 to Q2/2009. $SIZE_{i,t}$ is the logarithm of weekly average of the stock market capitalization measured in thousands of dollars. $STD_{i,t}$ is the standard deviation of daily stock return in a week. $TURNOVER_{i,t}$ is the logarithm of weekly stock trading turnover measured in thousands of dollars. $WEIGHT_{i,t}$ 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.

	$WLSI_{i,Spread}$		$WLSI_{i,Amihud}$	
	(1)	(2)	(3)	(4)
PILOT*DURING	0.14***	0.14***	0.21***	0.23***
	(3.34)	(3.34)	(4.14)	(4.14)
PILOT*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

Table 4.7 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 arbitrage activity increases for pilot component stocks and positively affects the liquidity

[31] The effect of these control variables on liquidity spillover between individual stocks and the ETF is shown in Appendix A3.

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.

4.5. Conclusion

Market liquidity has a crucial role in maintaining a well-functioning capital market. As a result, market liquidity dry-ups have drawn investors, researchers, and market regulators' significant interest. 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 the periods of market crisis or economic downturn, suggests that the risk of liquidity contagion between these two markets is high and should be monitored closely. Second, as short-sale constraints can reduce the magnitude of liquidity spillover, this measure can be used during a market crisis to lessen market liquidity's dry-ups.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

Name of candidate:	Son Pham
Name/title of Primary Supervisor:	Professor Nuttawat Visaltanachoti
Name of Research Output and full reference:	
Liquidity spillover between ETFs and their constituents	
In which Chapter is the Manuscript /Published work:	Chapter Four
Please indicate:	
• The percentage of the manuscript/Published Work that was contributed by the candidate:	70 percent
and	
• Describe the contribution that the candidate has made to the Manuscript/Published Work:	
Son made the research proposal about the topic. He gathered the data, conducted the empirical works, and wrote the paper. He submitted the paper to the International Review of Financial Analysis. During the weekly meetings, the	
For manuscripts intended for publication please indicate target journal:	
International Review of Financial Analysis	
Candidate's Signature:	Pham Duy Son Digitally signed by Pham Duy Son Date: 2021.06.21 17:29:39 +12'00'
Date:	
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Date:	

(This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis)

CHAPTER FIVE: CONCLUSION

This chapter concludes the thesis by summarising the major findings and implications for each of the three essays in Section 5.1 and suggesting areas for future research in Section 5.2.

5.1. Major findings and implications

5.1.1. Essay One

Despite the growing popularity of active ETFs, little is known about their liquidity. Most extant literature about ETF liquidity focuses on passive ETFs. However, passive and active ETFs have some unique aspects of portfolio management that could affect their liquidity differently. The first essay investigates the market liquidity of active equity ETFs listed on the US market and documents the determinants of their relative liquidity.

The key empirical findings of Essay One are as follows. First, the essay finds that active ETF liquidity is significantly lower than the weighted average liquidity of its underlying stocks. This finding contrasts with the relative liquidity of passive ETFs documented in the literature (Hedge and McDermott, 2004; Marshall, Nguyen, and Visaltanachoti, 2018; Broman and Shum, 2018). For active ETFs, the uncertainty of future holdings could be an essential source of adverse selection costs faced by ETF investors. As a result, active ETF liquidity may be lower than its underlying liquidity compared to passive ETF liquidity. Second, the essay reveals a negative correlation between ETF liquidity and its degree of diversification. This finding is in line with Pastor, Stambaugh, and Taylor's (2020) proposition of the trade-off between portfolio diversification and the liquidity of its underlying stocks. As investment managers try to diversify their portfolios, they tend to add more illiquid stocks. Because underlying liquidity can affect ETF liquidity through the creation/redemption mechanism, ETF liquidity can negatively affect diversification. Finally, the essay shows that the gap between ETF and underlying liquidity varies cross-sectionally and over time and can be explained by differences in size and volume between ETFs and their underlying portfolios, ETF age, and ETF pricing errors.

Overall, the essay provides evidence that the nature of fund management can affect the fund's market liquidity. The findings also help explain why the degree of diversification might come at the expense of ETF market liquidity and provide implications for ETF's sponsors in building their new products.

5.1.2. Essay Two

Several papers have investigated approaches to minimizing spread costs in stock transactions because of the critical role of transaction costs in determining investors' returns (Taylor, 2002; Wald and Horrigan, 2005; Groß-KlußMann and Hautsch, 2013). Given the growing importance of trading ETFs in recent years, Essay Two considers the extent to which traders can minimize transaction costs in trading ETFs via a systematic trading schedule.

The key empirical findings of the essays are as follows. First, using a large sample of 1,350 US ETFs between the period 2011-2017, I find a VAR model is superior to a moving average model in predicting intraday ETF bid-ask spreads. Second, the predictability of the model is dependent on ETF characteristics, sector, and style. Forecast errors are higher for ETFs with greater return volatility and smaller size. Third, using a set of macro-economic variables, the essay shows that those factors affect the ability to predict ETF bid-ask spread using the VAR model. An increase in market uncertainty or default risk lessens the forecast accuracy of the model.

More importantly, Essay Two assesses the economic significance of the VAR model from the perspective of both large and retail traders and provides significant implications for ETF investors. For large ETF traders who split their orders to hide their trading motivations, the essay shows that the average executed bid-ask spread using the VAR trading schedule is 7.4% and 8.29% lower than that of a naïve trading schedule or a moving average trading schedule, respectively. For retail ETF traders who do not split their orders, the essay reveals that trading at the close would be optimal to reduce bid-ask spread. Finally, when applying the VAR model to schedule trades, investors should consider the effect of spread volatility as the essay reveals that when an ETF is more volatile in the spread, it will have more room to minimize spread costs.

5.1.3. Essay Three

The dry-ups of liquidity in financial markets have been a growing concern from both investors and regulators because simultaneous evaporation of liquidity of many assets could create a spiral decline in assets' values and is a source of financial instability. Essay Three directly addresses the above concern by focusing on the liquidity spillover between ETF and the underlying market. Specifically, the essay documents the magnitude and determinants of liquidity spillover between an ETF and its underlying portfolio using daily data of the DIAMONDS ETF and its underlying stocks from 2002 to 2016.

The key empirical findings of the essay are as follows. First, I find the ETF liquidity and its underlying liquidity significantly affect each other. Using Diebold and Yilmaz's (2012) approach to model liquidity spillover, the essay reveals that past fluctuation of ETF liquidity is the most important contributor to the variation of underlying liquidity and vice versa. Furthermore, liquidity shocks from underlying stocks affect ETF liquidity more than in reverse. Second, the essay reveals that liquidity spillover is more pronounced during a market crisis, an economic downturn, or during a time of high volatility. Finally, the empirical findings of the essay indicate that liquidity spillover positively correlates with ETF arbitrage activity and is lower when short-sale constraints are in place.

The key results of Essay Three have two main policy implications. First, the essay provides evidence that the risk of liquidity contagion between ETF and the underlying market is substantial and should be monitored closely by the market watchers. Second, by reducing the magnitude of liquidity spillover, short sale constraints could be used during a market turmoil to avoid market liquidity's dry-ups.

5.2. Future areas of research

This thesis addresses several aspects of the portfolio liquidity topic. The first essay investigates the market liquidity of active ETFs, a renovated stock basket product, and provides evidence of the negative relationship between ETF's degree of diversification and ETF liquidity. It is promising for future research to empirically study this relationship in the scope of other stock basket products such as closed-end funds. If the negative linkage is held for other stock basket products, fund sponsors and fund managers should carefully consider the trade-off between diversification and liquidity in developing and managing their products.

The second essay uses the VAR model to predict the intraday liquidity of ETFs and finds that this model can assist large ETF traders to save their spread costs. This model assumes that the ETF bid-ask spread is dependent on a set of variables, including mid-quote volatility, trading volume, number of trades, and lagged bid-ask spread. However, the list of explanatory variables of the ETF bid-ask spread is not exhaustive. Depending on the availability of intraday data, the inclusion of other explanatory variables such as ETF pricing errors could improve the VAR model's predictability, which represents a possible venue for further research.

The final essay of this thesis investigates the transmission of liquidity between an ETF and its underlying portfolio. The empirical results suggest that this liquidity is significant and should be monitored by market regulators as a high level of spillover during the market crisis could lead to simultaneous evaporation of liquidity in both ETF and stock markets. Future studies may investigate the cross-sectional ETF characteristics that determine this liquidity spillover. Another possible avenue for future research is to employ the framework of liquidity spillover used in this essay to study the liquidity spillover between recently developed asset classes such as cryptocurrency with traditional investment asset classes.

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APPENDIX A
FOR ESSAY ONE

Appendix A.1. List of Active Equity ETFs in the Sample

Name	Ticker	Category	Inception Date	AUM in USD
AdvisorShares Dorsey Wright ADR ETF	AADR	Global Equity Large Cap	7/20/2010	141,271,534
First Trust North Amer Engy Infras ETF	EMLP	Energy Sector Equity	6/20/2012	1,937,778,251
Innovator IBD® 50 ETF	FFTY	US Equity Mid Cap	4/8/2015	190,672,097
AdvisorShares Madrona Domestic ETF	FWDD	US Equity Large Cap Blend	6/20/2011	27,978,476
EcoLogical Strategy ETF	HECO	Other Sector Equity	6/18/2012	8,527,413
US Market Rotation Strategy ETF	HUSE	US Equity Large Cap Blend	7/23/2012	64,715,438
PowerShares Active US Real Estate ETF	PSR	Real Estate Sector Equity	11/20/2008	24,585,332
AlphaMark Actively Managed Small Cap ETF	SMCP	US Equity Small Cap	4/20/2015	26,470,639
SPDR® MFS Systematic Core Equity ETF	SYE	US Equity Large Cap Value	8/1/2014	7,238,824
SPDR® MFS Systematic Growth Equity ETF	SYG	US Equity Large Cap Growth	8/1/2014	46,415,741
Cambria Shareholder Yield ETF	SYLD	US Equity Mid Cap	5/13/2013	127,863,907
SPDR® MFS Systematic Value Equity ETF	SYV	US Equity Large Cap Value	8/1/2014	6,404,054
AdvisorShares Wilshire Buyback ETF	TTFS	US Equity Mid Cap	4/10/2011	129,388,740
Reaves Utilities ETF	UTES	Utilities Sector Equity	9/23/2015	15,136,456
Validea Market Legends ETF	VALX	US Equity Mid Cap	10/12/2014	25,234,462
WBI Tactical SMGD Shares	WBIA	US Equity Mid Cap	8/25/2014	41,222,723
WBI Tactical SMV Shares	WBIB	US Equity Mid Cap	8/25/2014	71,204,184
WBI Tactical SMY Shares	WBIC	US Equity Mid Cap	8/25/2014	60,704,216
WBI Tactical SMQ Shares	WBID	US Equity Mid Cap	8/25/2014	74,956,085
WBI Tactical LCGD Shares	WBIE	US Equity Large Cap Growth	8/25/2014	47,626,904
WBI Tactical LCV Shares	WBIF	US Equity Large Cap Blend	8/25/2014	79,273,244
WBI Tactical LCY Shares	WBIG	US Equity Large Cap Blend	8/25/2014	81,146,163
WBI Tactical LCQ Shares	WBIL	US Equity Large Cap Blend	8/25/2014	47,419,027

APPENDIX B
FOR ESSAY TWO

Appendix B.1. Time-Weighted Bid-Ask Spread and Dollar Volume-Weighted Effective Spread

Notes: This table presents the values of time-weighted bid-ask spread (*BAS*) and dollar volume-weighted effective spread (*ESpread*) of ETF in the sample. These figures are calculated every 15 minutes and averaged for daily and yearly calculation. In Panel A, the spreads are reported yearly over the research period. In Panel B, the spreads are presented according to seven ETF sectors classified by Morningstar.

Panel A. By Year

Year	Number of ETFs	BAS (in bps)	ESpread (in bps)
2011	402	44.04	24.41
2012	466	45.61	24.40
2013	551	40.04	20.43
2014	629	37.11	20.78
2015	827	43.87	26.33
2016	941	48.71	26.57
2017	1,245	37.48	20.26

Panel B. By ETF Sector

ETF Sector	Number of ETFs	BAS (in bps)	ESpread (in bps)
Allocation	30	46.49	24.12
Alternative	271	44.11	27.59
Commodities	25	49.28	26.11
Convertibles	2	141.67	72.36
Equity	796	41.72	22.76
Fixed Income	199	40.13	20.00
Tax Preferred	27	43.41	21.40

Appendix B.2. Intraday Patterns of ETF Liquidity

Notes: This table reports the regression results of the following equation:

$$S_{i,j,d}=\alpha + \sum_{j=1}^{4}\beta_j D_j + \sum_{j=25}^{26}\beta_j D_j + Exch\_Dummy_i + \varepsilon_{i,i,d} \quad \text{(B.2)}$$

where $S_{i,j,d}$ is the spread of ETF *i* during interval *j* of day *d* with spread can be either time-weighted bid-ask spread or dollar volume-weighted effective spread and D_j is the dummy variable for time interval *j*. D_j has a value of 1 if it is the *j*th interval and 0 otherwise. Each trading day is divided into 26 15-minute time intervals. $Exch\_Dummy_i$ has a value of 1 if ETF *i* listed on NASDAQ and 0 if listed on NYSE. ***, **, and * represent statistical significance at the 1%, 5% and 10%, respectively.

Independent Variables	BAS (1)	ESpread (2)
D_1	24***	17.6***
	(18.12)	(10.17)
D_2	5.2***	4.82***
	(4.78)	(5.13)
D_3	0.39	2.36***
	(0.51)	(2.84)
D_4	-0.4	1.17***
	(-0.57)	(2.33)
D_{25}	-4.6***	-2.0***
	(-9.84)	(-3.20)
D_{26}	-7.6***	-2.6***
	(-16.81)	(-6.18)
Exchange_Dummy	2.21***	1.9***
	(4.70)	(6.77)
Intercept	41.13***	22.05***
	(205.4)	(143.6)

APPENDIX C
FOR ESSAY THREE

Appendix C.1. ETF and Underlying Liquidity

Notes: Figures C.1.1 and C.1.2 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.

Figure C.1.1. Bid-Ask Spread of the DIAMONDS ETF and the Underlying Portfolio

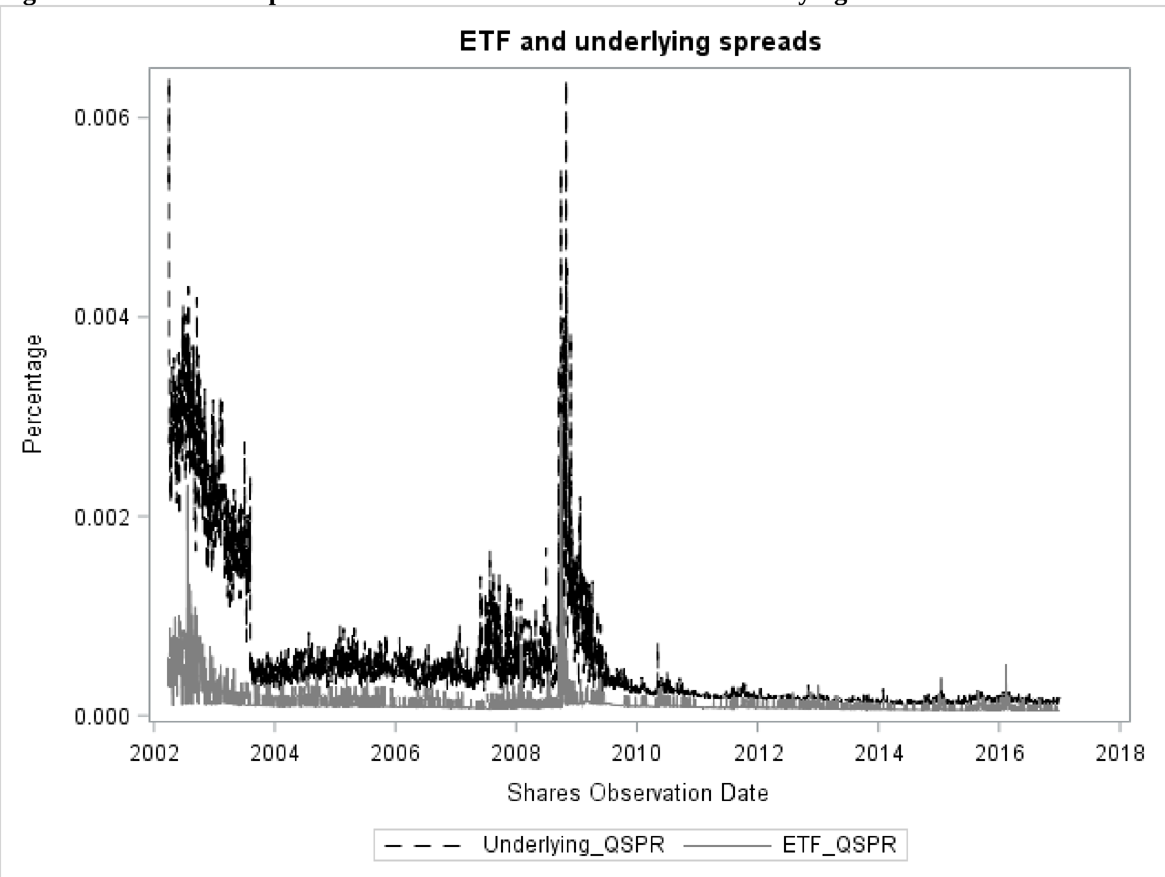
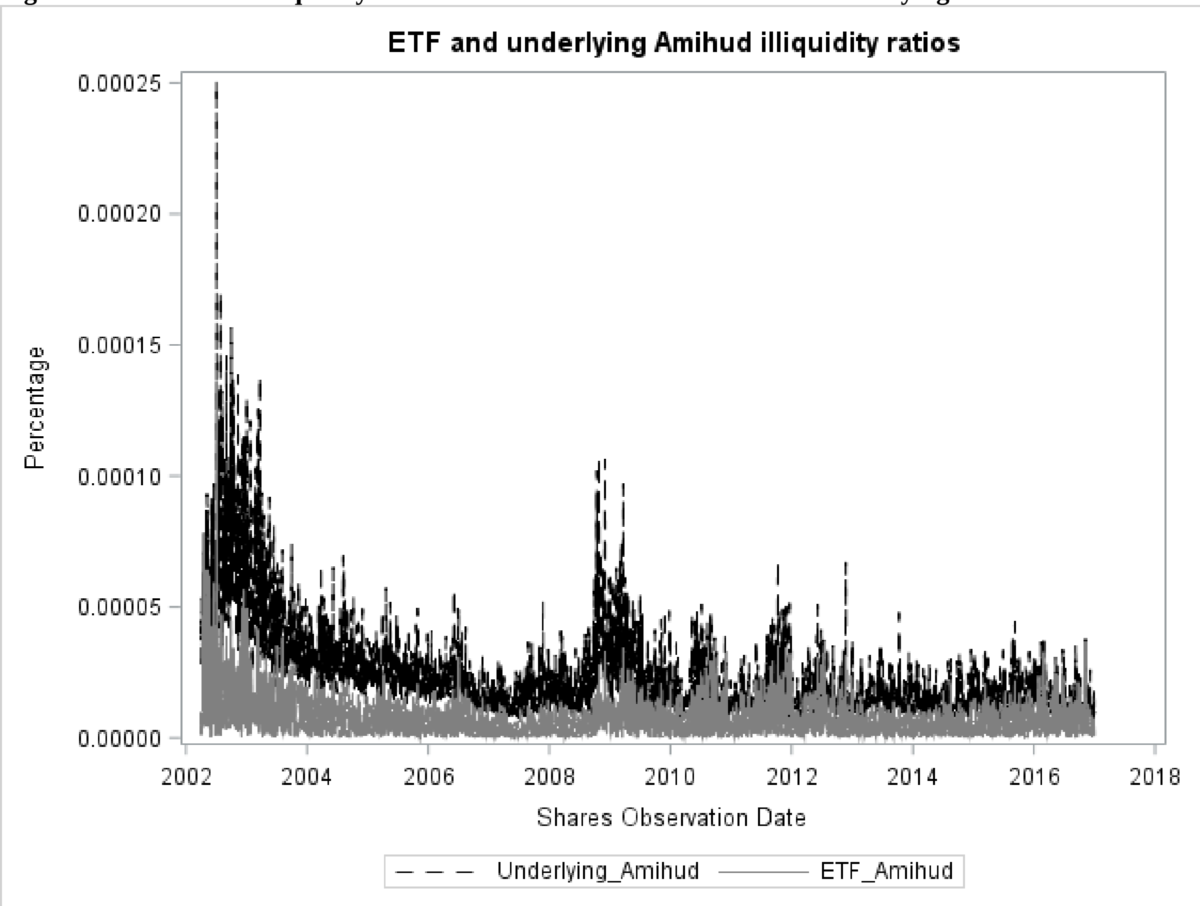


Figure C.1.2. Amihud Illiquidity Ratio of the DIAMONDS ETF and the Underlying Portfolio



Appendix C.2. Results of VAR Model of Individual Component Stocks of ETF

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

$$ETF_t = \sum_{j=1}^{k} \beta_j ETF_{t-j} + \sum_{j=1}^{k} \gamma_j Stock_{i,t-j} + \varepsilon_t \quad \text{(C1)}$$

$$Stock_{i,t} = \sum_{j=1}^{k} \beta_j Stock_{i,t-j} + \sum_{j=1}^{k} \gamma_j ETF_{t-j} + \varepsilon_t \quad \text{(C2)}$$

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.

Stock Ticker	Bid-ask spread		Amihud	
	Test 1	Test 2	Test 1	Test 2
AA	149.26***	115.79***	31.96***	5.78*
AAPL	4.21	6.85**	1.97	5.26
AIG	2.72	11.51***	5.85*	12.76***
AXP	70.38***	150.96***	36.06***	4.08
BA	119.01***	164.31***	88.96***	8.07*
BAC	1.10	11.95***	7.13*	8.89**
C	88.25***	45.67***	9.62**	14.95***
CAT	51.35***	194.41***	84.17***	16.28***
CC	0.51	1.10	0.56	1.27
CSCO	8.44**	13.32***	1.44	0.34
CVX	11.39***	24.36***	10.47*	10.25*
DD	159.32***	195.86***	15.39***	36.3***
DIS	297.11***	151.35***	132.74***	15.59***
EK	9.90***	20.45***	7.35**	1.01
GE	117.70***	221.84***	54.16***	33.07***
GM	5.67*	11.99***	0.92	1.48
GS	2.88	6.74*	1.47	3.21
HON	80.76***	55.35***	24.10***	8.64**
HD	201.21***	146.06***	59.97***	20.87***
HPQ	83.39***	130.81***	59.85***	20.75***
IBM	73.42***	129.06***	19.41***	23.13***
INTC	7.98**	10.95**	29.33***	8.25*
IP	38.14***	5.35	0.84	0.56
JNJ	40.10***	138.55***	64.22***	45.36***
JPM	44.73***	134.83***	99.78***	22.46***
KO	369.2***	227.54***	51.11***	36.16***
MCD	130.69***	140.83***	65.22***	13.84***
MDLZ	9.34**	60.09***	0.79	2.02
MMM	54.69***	197.08***	2.27	4.39
MO	73.77***	109.96***	13.48***	30.70***
MRK	17.57***	76.99***	39.35***	21.34***
MSFT	1.80	3.34	5.62*	8.92***
NKE	6.3*	7.34*	4.32	12.68***
PFE	53.84***	43.43***	39.21***	42.23***
PG	78.33***	139.43***	44.77***	34.26***
T	110.68***	203.15***	101.21***	8.83*
TRV	3.34	7.45**	4.90	12.57***

UNH	30.59^{***}	24.23^{***}	4.55	2.82
UTX	83.04^{***}	150.56^{***}	81.73^{***}	29.61^{***}
V	7.87^{***}	2.92	24.1^{***}	9.59^{*}
VZ	31.92^{***}	28.43^{***}	0.71	4.71
WMT	90.47^{***}	173.22^{***}	98.43^{***}	66.23^{***}
XOM	54.54^{***}	283.79^{***}	103.19^{***}	9.61^{**}

Appendix C.3. Granger Causality Tests with Exogenous Variables

Notes: 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:

$$X_t = \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + VIX_t + MDT_t + \varepsilon_t \tag{C3}$$

$$Y_t = \sum_{j=1}^{k} \beta_j Y_{t-j} + \sum_{j=1}^{k} \gamma_j X_{t-j} + VIX_t + MDT_t + \varepsilon_t \tag{C4}$$

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 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 $Amihud_{U,t}$). 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.

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

	$QSPR_E$	VOL_E	RET_E	$QSPR_U$	VOL_U	RET_U
$QSPR_E$		14.82	14.22	16.45	7.27	17.39
		(0.005)	(0.007)	(0.003)	(0.12)	(0.002)
VOL_E	103.11		9.37	19.57	24.27	9.64
	(0.0001)		(0.05)	(0.0006)	(0.0001)	(0.05)
RET_E	24.21	288.6		27.04	257.45	0.76
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.94)
$QSPR_U$	287.10	45.84	15.54		48.98	19.46
	(0.0001)	(0.0001)	(0.004)		(0.0001)	(0.0001)
VOL_U	106.5	55.41	18.37	11.39		18.13
	(0.0001)	(0.0001)	(0.001)	(0.03)		(0.001)
RET_U	22.14	291.2	5.19	28.37	252.5	
	(0.0002)	(0.0001)	(0.29)	(0.0001)	(0.0001)	

Panel B. Using Amihud illiquidity as liquidity measure

	$Amihud_E$	VOL_E	RET_E	$Amihud_U$	VOL_U	RET_U
$Amihud_E$		37.99	6.18	45.08	18.20	5.94
		(0.0001)	(0.18)	(0.001)	(0.001)	(0.20)
VOL_E	128.10		9.37	142.07	24.27	9.64
	(0.0001)		(0.05)	(0.0001)	(0.0001)	(0.05)
RET_E	55.59	288.6		98.88	257.45	0.76
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.94)
$Amihud_U$	54.82	32.88	11.62		21.95	11.68
	(0.001)	(0.001)	(0.02)		(0.001)	(0.02)
VOL_U	108.61	55.41	18.37	115.76		18.13
	(0.0001)	(0.0001)	(0.001)	(0.0001)		(0.001)
RET_U	51.72	291.2	5.19	92.57	252.5	
	(0.0001)	(0.0001)	(0.27)	(0.0001)	(0.0001)	

Appendix C.4. Granger Causality Tests with Modified Amihud Illiquidity

Notes: 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:

$$X_t = \sum_{j=1}^{k} \beta_j X_{t-j} + \sum_{j=1}^{k} \gamma_j Y_{t-j} + \varepsilon_t \quad \text{(C5)}$$

$$Y_t = \sum_{j=1}^{k} \mu_j Y_{t-j} + \sum_{j=1}^{k} \lambda_j X_{t-j} + \phi_t \quad \text{(C6)}$$

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 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: $VOL_{U,t}$). *MOD_AMI* is the modified Amihud illiquidity, which is used as the liquidity proxy for the ETF and its underlying portfolio. It 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.

	MOD_AMI_E	VOL_E	RET_E	MOD_AMI_U	VOL_U	RET_U
MOD_AMI_E		42.98 (0.0001)	15.98 (0.10)	19.59 (0.03)	33.58 (0.0002)	15.04 (0.13)
VOL_E	37.78 (0.0001)		14.91 (0.14)	18.64 (0.05)	31.01 (0.0001)	10.86 (0.36)
RET_E	60.04 (0.0001)	339.79 (0.0001)		89.35 (0.001)	298.36 (0.0001)	21.06 (0.20)
MOD_AMI_U	48.7 (0.0001)	36.44 (0.0001)	10.82 (0.37)		29.62 (0.001)	10.51 (0.39)
VOL_U	37.86 (0.0001)	42.74 (0.0001)	32.92 (0.0003)	18.74 (0.05)		30.37 (0.0001)
RET_U	58.15 (0.0001)	343.4 (0.0001)	23.40 (0.15)	87.33 (0.0001)	292.27 (0.0001)	

Appendix C.5. Summary of Dependent Variables in Section 4

Notes: 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.

Variables	Mean	Median	Std.Dev	Min	Max
ETF_CAP	943.84	902.78	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	344.3
SHORTRATE	-0.0012	0	0.098	-1.08	0.35
TERMSPREAD	-0.001	-0.01	0.165	-0.79	1.39
DEFAULTSPREAD	-0.002	0.00	0.087	-0.52	0.74
YTD_STD	0.024	0.015	0.027	0	0.214

Appendix C.6. Stock-level Determinants of Liquidity Spillover

Notes: This table reports the regression results of the following equation:

$$WLSI_{i,t} = \alpha + \beta_1 SIZE_{i,t} + \beta_2 STD_{i,t} + \beta_3 TURNOVER_{i,t} + \beta_4 WEIGHT_{i,t} + \varepsilon_t \quad (C7)$$

where $WLSI_{,t}$ is the *Weekly Liquidity Spillover Index* between component stock *i* with the DIAMONDS ETF using bid-ask spread or Amihud illiquidity ratio as liquidity measure. $SIZE_{i,t}$ is the logarithm of the weekly average of the stock market capitalization measured in thousands of dollars. $STD_{i,t}$ is the standard deviation of daily stock return in a week. $TURNOVER_{i,t}$ is the logarithm of weekly stock trading turnover measured in thousands of dollars. $WEIGHT_{i,t}$ is the weight of stock *i* in the ETF measured 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.

	$WLSI_{i,Spread}$				$WLSI_{i,Amihud}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SIZE	0.002 (0.08)	0.07 (1.47)	0.01 (0.41)	0.10* (1.79)	-0.001 (-0.11)	0.06*** (4.23)	-0.02*** (-3.04)	0.04** (2.37)
STD	7.01*** (3.98)	8.13*** (4.32)	6.87*** (3.68)	7.97*** (4.02)	10.45*** (20.49)	11.9*** (21.75)	11.82*** (21.98)	13.40*** (23.51)
TURNOVER	-0.07* (-1.83)	-0.086* (-1.81)	-0.05 (-1.18)	-0.067 (-1.14)	-0.12*** (-10.33)	-0.15*** (-10.68)	-0.17*** (-12.76)	-0.23*** (-13.91)
WEIGHT	0.003 (0.26)	-0.02 (-0.60)	0.001 (0.12)	-0.02 (-0.99)	0.004 (1.09)	-0.01* (-1.8)	0.01** (2.54)	-0.01 (-1.45)
Intercept	-0.08 (-0.23)				0.02 (0.18)			
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	20,254	20,254	20,254	20,254	20,254	20,254	20,254	20,254
R-squared	0.001	0.001	0.001	0.0012	0.020	0.024	0.034	0.038