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Liquidity risk and exchange-traded fund returns, variances, and tracking errors☆

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ABSTRACT

We investigate the effect of exchange-traded fund (ETF) liquidity on ETF tracking errors, returns, and volatility in the US. We find that illiquid ETFs have large tracking errors. The effect is more pronounced when underlying assets are less liquid. Returns and liquidity of illiquid ETFs are more sensitive to underlying index returns or ETF market liquidity, or both. Thus, a positive liquidity premium exists in US ETF markets. The ETF variance could be larger than its net asst value variance owing to infrequent trading. In summary, illiquid ETFs are more likely to deviate from their underlying indexes and could be riskier than underlying portfolios.

1. Introduction

US exchange-traded funds (ETFs), introduced in 1993, have grown significantly in recent years. At the end of 2016, their market size was about $3 trillion, accounting for nearly 30% of the dollar trading volume and 23% of the share volume in US stock markets. ETFs have grown to become the most popular asset class for many institutional and individual investors.[1] Despite such rapid growth, most of the money flowing into ETFs is concentrated in a few well-known ETFs. For example, at the end of 2012, the top three (ten) ETFs accounted for 46.7% (61.5%) of the total ETF dollar trading volume (Figs. 1–3). In addition, the assets under management (AUM) of the top 10 ETFs accounted for 36% of the total AUM in the US ETF market. The lack of liquidity in non-popular ETFs could prevent market makers from developing proper markets and, consequently, increase transaction costs for ETF investors. This study sheds light on secondary market liquidity issues by examining how ETF liquidity affects the price formation of ETFs, especially relative to their benchmark indexes or net asset values (NAVs).

An ETF is designed to provide an indirect investment opportunity for particular markets, countries, or industries

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[1] From 2007 to 2016, $1.2 trillion from active mutual funds were withdrawn and ETF investment reached $1.4 trillion (Wigglesworth, 2017).

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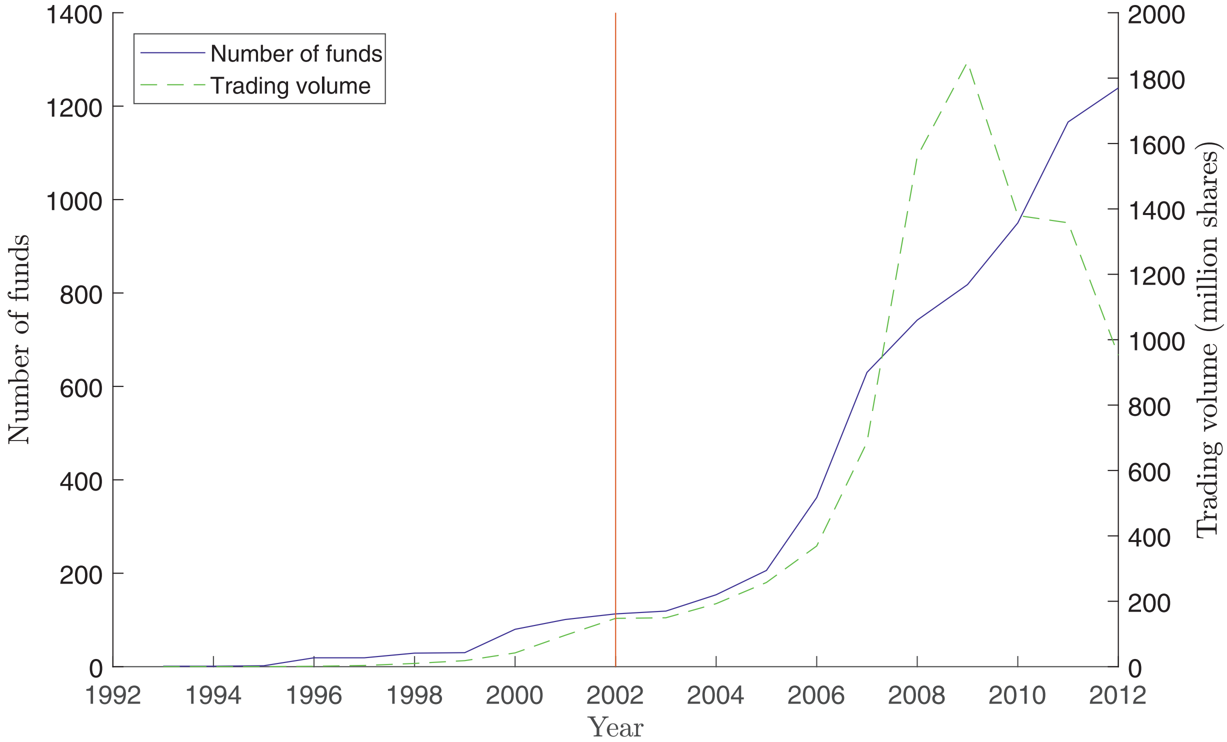

Fig. 1. The number of funds and market value of exchange-traded funds (ETFs). This figure illustrates the number of ETFs and trading volume of US ETFs at year-end from 1993 to 2012. The solid line plots the number of funds available at the end of each year. The dotted line plots the share trading volume of funds at the end of each year. The solid vertical line denotes 2002.

by replicating a specific representative index. Index-based ETFs allow investors to access foreign markets or a variety of asset classes at relatively low transaction costs. The fundamental risk of the ETF arises from the market risk associated with the underlying index that it follows. In addition to the index risk, investors can bear risk if the ETF fails to track its underlying index correctly. In other words, the deviations of ETF returns from the index or NAV returns could be an additional risk for ETF investors. In general, ETFs are traded on major stock exchanges, but their shares are created and redeemed in the primary market. This unique structure results in the existence of two prices for a single asset: one is ETF market prices determined on stock exchanges and the other is its NAV calculated based on the value of underlying securities. Intuitively, a no-arbitrage condition implies that the daily ETF returns and the NAV returns must be identical. However, various factors can widen the gaps between them. This study is interested in the secondary market liquidity, which could affect the ETF returns and volatility, as well as ETF tracking errors.

ETFs are fundamentally similar to, but are not, mutual funds.[2] They are structured, managed, and regulated just like traditional mutual funds.[3] Different from conventional open-ended mutual funds, ETFs are traded continuously on regular exchanges, like regular stocks are. In addition, ETFs are similar to closed-end funds (CEFs) in that they are traded on exchanges.[4] Unlike CEFs, the total number of shares can be increased or decreased depending on market demand and supply. In other words, ETFs are designed to combine the creation and redemption process of open-end funds with the continuous trading of the CEFs. These characteristics form the crucial mechanism that enables the facilitation of arbitrage between the ETF and its underlying assets. The arbitrage activities of authorized participants (APs), who are responsible for creating or redeeming ETF shares or constructing the underlying ETF portfolios, should eliminate the ETF return deviations from

[2] The Securities an Exchange Commission (SEC) defines ETFs as "SEC-registered investment companies that offer investors a way to pool their money in a fund⋯. ETFs are not mutual funds. But, they combine features of a mutual fund" For more details, see http://www.sec.gov/answers/etf.htm

[3] Exchange-traded notes (ETNs) and exchanged-traded commodities (ETCs) are similar to ETFs. An ETN is a senior unsecured debt obligation designed to track the total return of an underlying index or benchmark. ETNs are exposed to both the market risk of linked indexes and the credit risk of the issuer. An ETC holds physical commodities or currencies. Neither ETNs nor ETCs are registered under the Investment Company Act of 1940, but they are regulated under the Securities Act of 1933. Since Ben-David et al. (2017) report that the value of ETFs accounts for about 95% of the entire US ETP market, we exclude both ETNs and ETCs from our sample for consistent analysis.

[4] The CEFs are also listed and traded in stock exchanges like common stocks. The CEFs typically trade at a discount to the portfolio value. This is called the closed-end fund discount puzzle. See Lee et al. (1991) and Pontiff (1996) for details.

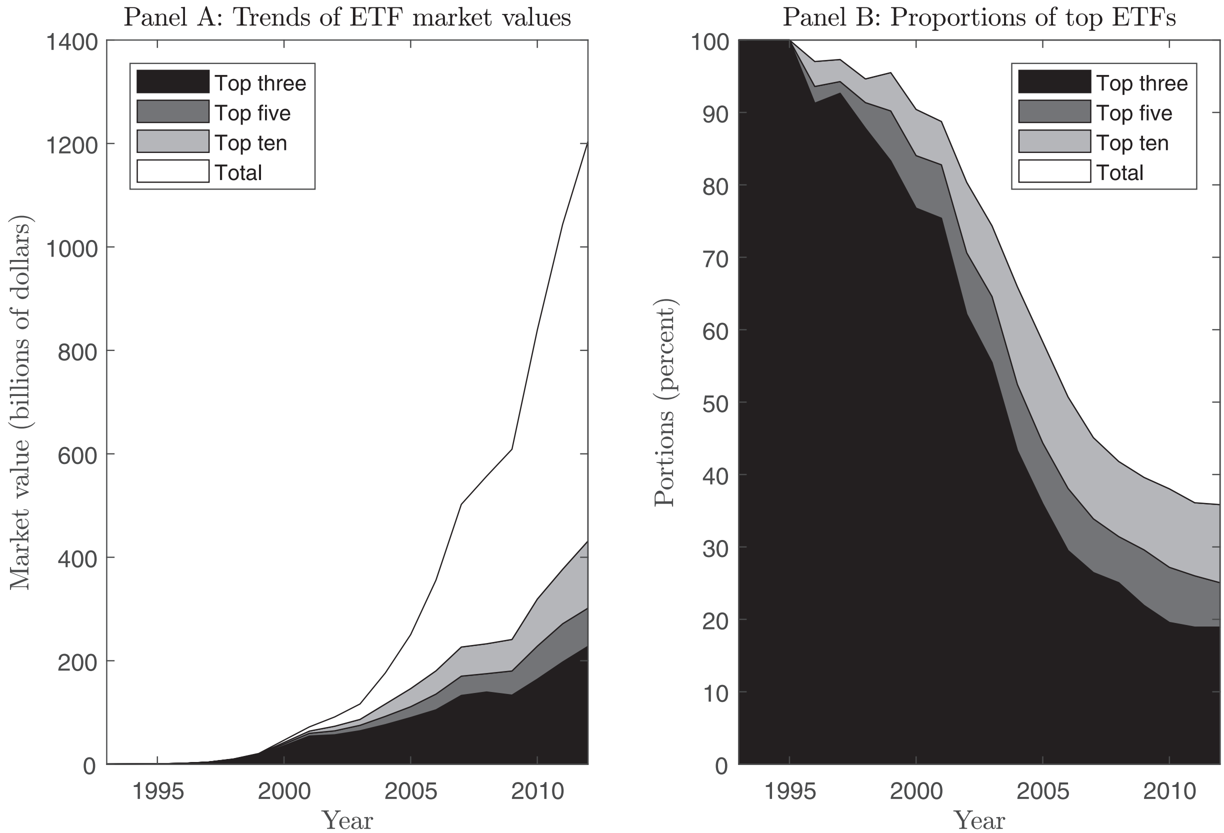

Fig. 2. Market value by top exchange-traded funds (ETFs). This figure plots the market values of the top three, five and ten ETFs in the US ETF market by calendar year. For each ETF, we compute the annual average daily net asset values and the total market values by summing all average values for each ETF. We compute the portions of the top three (five, ten) ETFs by summing the top three (five, ten) values divided by total market value.

its NAV returns.[5] This arbitrage mechanism can be limited if either ETFs or the underlying assets are less liquid.

The lack of liquidity in the underlying assets can result in tracking errors because low liquidity in underlying assets could discourage APs from replicating the index at the time of trading the basket securities. Moreover, the lack of liquidity in ETF securities causes a mispricing problem for its NAV or index returns, because arbitrage activities must take place simultaneously on both ETF and underlying asset markets. When the ETF is less liquid, APs could find difficult trading at desired prices at the time of setting arbitrage positions or profit realization through unwinding. In this situation, APs could be reluctant to actively engage in arbitrage trading for low liquidity ETFs, or they could require additional returns even when available for arbitrage trading. As a result, APs can strategically wait for a tracking error (i.e., large arbitrage opportunity) to widen or increase the bid-ask spread to meet the additional required return on risk. This situation can cause investors to pay higher transaction costs and, thus, should lead to a case in which the elimination of the tracking error is delayed. The recently introduced NAV-based trading, or the ETF liquidity program of the Nasdaq and NYSE, reflects investors' concern about the liquidity and tracking errors of the ETF market.[6] Thus, these recent attempts suggest that liquidity provisions and tracking error problems are important issues in the ETF market and, hence, investigating their relations is critical.

[5] According to Antoniewicz and Heinrichs (2015), there are about 34 APs, on average, for each ETF in the US ETF industry. The number of APs is larger for an ETF that is large and that invests in US assets. Regarding daily trading activity, APs conducted about 90% of their trading activity on the secondary market during 2005 and 2006.

[6] In 2014, Euronext launched a new platform that allows ETFs to be traded at the end-of-day NAV of the fund once a day. Pedro Fernandes, head of European ETPs at Euronext, said, "For investors who have neither the time nor the infrastructure to trade intraday, this can be a good solution, as you get NAV, plus or minus the creation and redemption costs, on exchange and you get invested without having to manage whether it is the right moment of the day to trade a product." For more details about Euronext NAV trading, see https://www.euronext.com/nl/content/attachment/nav-trading-facility-overview. However, there are some challenges for NAV-based trading (Packham and Pingali, 2016). On September 3, 2013, the NYSE launched a pilot program whereby issuers can pay between $10,000 and $40,000 per ETF annually to be part of the ETF program, specifically for new and less active ETFs. According to the program, liquidity providers can receive fixed quarterly payments if they meet monthly quoting obligations. In the same period, the Nasdaq launched a similar program called the Market Quality Program.

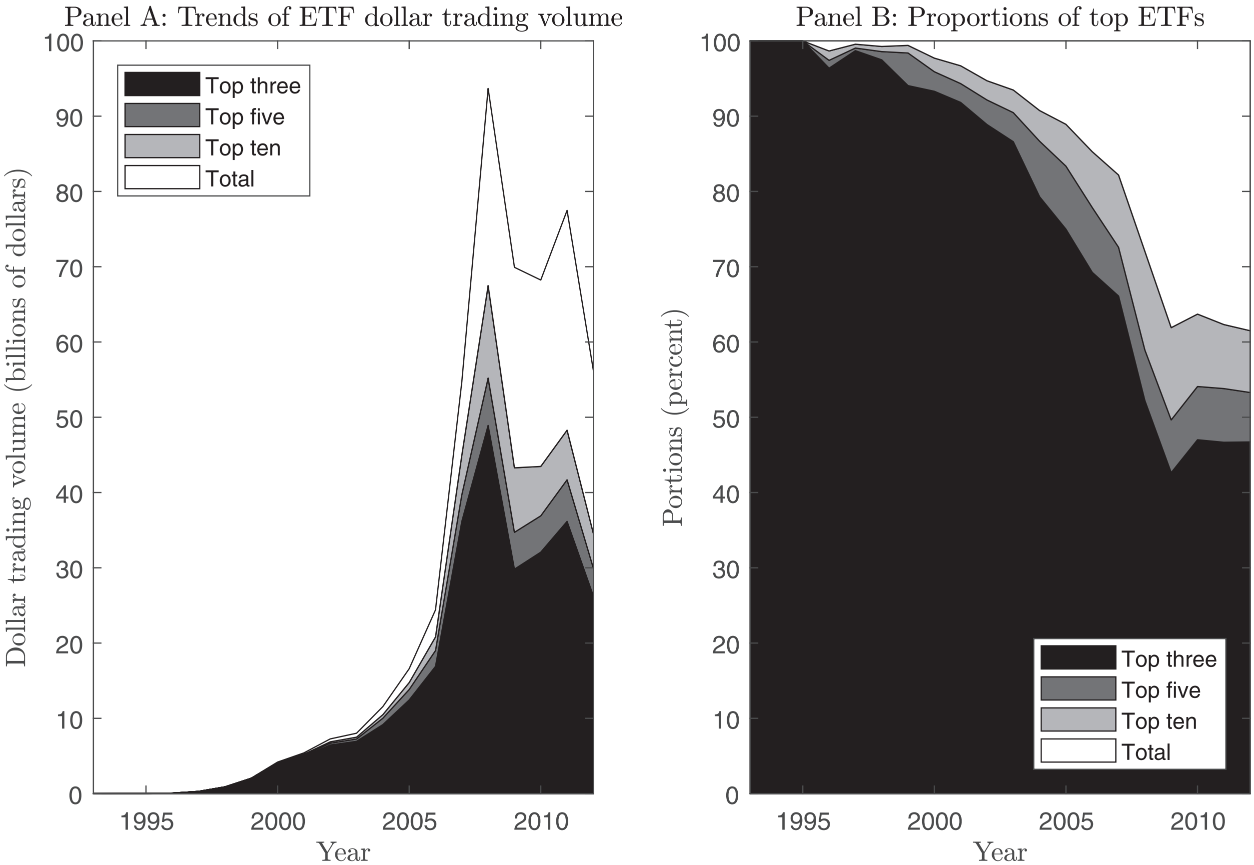

Fig. 3. Trading volume by top exchange-traded funds (ETFs). This figure plots the trading volumes of the top 3 (5, 10) ETFs in the US ETF market by calendar year. For each ETF, we compute the annual average daily trading volumes and the total market trading volumes by summing all average values for each ETF. We compute the portions of the top 3 (5, 10) ETFs by summing the top 3 (5, 10) values divided by total market trading volume.

Many previous studies show the effect of liquidity on asset returns and suggest that systematic liquidity risk is priced in asset returns.[7] For example, Acharya and Pedersen (2005) develop a liquidity-adjusted capital asset pricing model (LCAPM) and find that individual asset returns are significantly affected by liquidity risk. Pastor and Stambaugh (2003) suggest that individual stock returns are affected by aggregate market liquidity, which is a cross-sectional average of the individual return reversals. In addition to studies on the relations between asset returns and liquidity in US equity markets, numerous studies investigate the effect of liquidity on asset returns in other markets or asset categories: emerging markets (Bekaert et al., 2007), global markets (Lee, 2011), hedge funds (Getmansky et al., 2004; Sadka, 2010), initial public offering markets (Eckbo and Norli, 2005), and closed-end funds (Cherkes et al., 2009).

Only a few studies analyze the effect of liquidity on ETFs, although the literature on ETFs is growing (Madhavan, 2014; Ben-David et al., 2017). Related existing studies consider ETF pricing problems on the Flash Crash of May 6, 2010 (Borkovec et al., 2010; Madhavan, 2012), the interactions between the ETF market and the underlying securities markets (Cespa and Foucault, 2014; Bhattacharya and O'Hara, 2017; Dannhauser, 2017; Israeli et al., 2017; Ben-David et al., 2018; Da and Shive, 2018), whether the ETF is priced efficiently with respect to its NAV or index (Elton et al., 2002; Engle and Sarkar, 2006), the relations between ETFs and traditional funds (Huang and Guedj, 2009; Barnhart and Rosenstein, 2010; Agapova, 2011), and the ETF investors' behavior (Clifford et al., 2014; Wermers and Xue, 2015; Bhattacharya et al., 2017). Only a few studies analyze the effect of ETF liquidity. For example, Borkovec et al. (2010) report that a sharp increase in the bid-ask spread leads to failure of ETF price discovery during the Flash Crash. Cespa and Foucault (2014) develop a theoretical model showing that the lack of liquidity in ETFs can lead to an increase in the uncertainty of the underlying securities, which results in a decrease in the liquidity of the corresponding ETFs. To the best of our knowledge, no empirical studies cover the effects of liquidity on ETF returns and tracking errors comprehensively.

We begin our analysis by studying the relations between ETF liquidity and ETF tracking errors. We present evidence that tracking errors and ETF illiquidity are

[7] For example, see Amihud and Mendelson (1986), Huang and Stoll (1994), Brennan and Subrahmanyam (1996), Chordia et al. (2001) and Amihud (2002). For further information about empirical studies on liquidity, see Holden et al. (2014).

positively related at both daily and yearly levels.[8] In particular, our empirical results show that various ETF illiquidity measures have consistently positive relations with ETF tracking errors. We further test the causal link from illiquidity to tracking errors by exploiting liquidity shocks of threshold stocks as an instrumental variable. According to Evans et al. (2017), failures-to-deliver (FTDs) are associated with liquidity changes, and excessive consecutive FTDs could force ETFs to be threshold stocks when accompanied by liquidity shocks. Our empirical analysis confirms that the instrumental variable regressions with various liquidity measures show a causal link between ETF illiquidity and ETF tracking errors.

We also examine the effect of ETF illiquidity on ETF tracking errors depending on how ETFs are structured. Our empirical analysis shows that tracking errors of the in-kind type of ETFs are less sensitive to ETF illiquidity than other types of ETFs are. These results imply that ETF companies could choose the in-kind method strategically instead of the cash method when they are able to easily construct the assets of the index at the time of the fund inception. We employ ETF portfolio holding data to examine the extent to which ETF illiquidity affects ETF tracking errors owing to liquidity differences in underlying assets. We select only non-leveraged US stocks-based ETFs to investigate the effects of underlying asset illiquidity and ETF illiquidity on the tracking errors. We find that both underlying asset illiquidity and ETF illiquidity affect ETF tracking errors. More important, the analysis confirms that illiquidity of ETFs investing in less liquid assets can have a greater impact on their tracking errors even if they hold the same asset classes of the same market. In summary, our overall empirical results confirm that ETF illiquidity is a very important factor affecting ETF tracking errors.

Next, we investigate whether liquidity shocks to ETFs are priced based on the LCAPM of Acharya and Pedersen (2005). We construct ten portfolios sorted by ETF liquidity or by various measures of tracking errors. Consistent with the regression analysis, the sorted portfolios provide evidence that ETF illiquidity is positively related to ETF tracking errors. Moreover, the relations between ETF illiquidity and tracking errors are persistent over time. We further estimate ETF liquidity betas to investigate whether any systematic risk factors associated with liquidity exist. The estimated results show that illiquid ETFs tend to reveal large absolute liquidity betas and have a positive liquidity risk premium. In other words, illiquid ETFs returns tend to be more sensitive to either market liquidity or the market return. In addition, using pre-estimated betas, we estimate the liquidity premium using the generalized method of moments (GMM). The annualized return due to liquidity risk is approximately 0.14%, suggesting a positive liquidity premium in the ETF market.

Finally, we examine whether infrequent trading affects ETF variance relative to the NAV variance, which is presumed to be the true variance of the ETF. To examine the effect of secondary market liquidity on volatility, we extend the Lo and MacKinlay (1990) econometric model to derive ETF variance with respect to the NAV variance. The difference between the ETF variance and NAV variance can be interpreted as volatility arising from the trading effect in the secondary market, in addition to the inherent risk arising from the underlying asset portfolios. Considering the autocorrelation of the index return, we show that the non-trading probability is positively related to the increase in the ETF variance with respect to the NAV variance. In other words, the derived equation shows that the ETF return variance can be expressed as the sum of the NAV return variance and the additional term caused by infrequent trading of the ETF security in the secondary markets. Furthermore, our empirical analysis confirms that non-trading probability is positively related to the variance difference between ETF returns and NAV returns. These results suggest that investors investing in illiquid ETFs could bear additional unnecessary risk arising from the secondary market trading instead of investing directly in underlying portfolios or similar mutual funds.

In summary, the results of this research reveal that lack of ETF liquidity is related to its expected return and variance, as well as ETF tracking errors. To the best of our knowledge, ours is the first comprehensive empirical study to examine the liquidity effects in the ETF market in relation to returns, risks, and tracking errors by using the entire US ETF market data. Extending the literature of liquidity effects on asset returns, this study shows that the liquidity of ETFs affects their returns or volatility. In other words, the lack of liquidity in the ETF causes APs to increase the transaction costs for arbitrage trading, for failing to resolve the tracking errors immediately, and for failing to follow the index properly, thereby resulting in failure to meet the objectives of ETF investors. As a result, trading illiquid ETFs can increase the cost of market making and raise the transaction costs of ETF investors.

The remainder of the paper is organized as follows. Section 2 provides data sources and variable constructions. Section 3 investigates whether ETF liquidity is related to ETF tracking errors. Section 4 provides the estimation results of the LCAPM and the cross-sectional evidence for liquidity risk. Section 5 derives the closed form of ETF variance relative to ETF NAV variance when ETFs are not traded frequently and compares both variances. Section 6 concludes.

2. Data and variables

This section introduces the data construction procedure. The data used in this paper includes all ETFs listed on the major US stock exchanges from 1993 to 2012. To ensure data integrity, we cross-check the information using the various data sources.

[8] ETF tracking errors are similar to the relations between futures and underlying asset prices. Roll et al. (2007) study the interactions between illiquidity and the futures basis in the Standard & Poors 500 futures markets. They conclude that the contemporaneous shocks to the futures basis and bid-ask spreads are positively correlated. Nashikkar et al. (2011) study the effect of the liquidity of corporate bonds liquidity on the basis between the par-equivalent bond yield spread and the credit default swap spread.

2.1. ETF data

The ETF sample used in this study contains all ETFs that have ever been listed and traded on the major US stock exchanges from 1993 to 2012. The country of domicile for each ETF is limited to the US at the inception date. The initial data also include all delisted ETFs that were traded in the US market during the sample period. All ETF data are extracted from the Bloomberg database. Bloomberg has daily historical prices for ETFs, NAVs, and the underlying indexes, as well as institutional details about the ETFs.[9] Bloomberg provides additional time series data of NAVs and shares outstanding provided under each ETF ticker by assigning separate bloomberg symbols for shares outstanding or NAV. We attempt to build as complete a data set as possible by comparing and gathering all available information provided by Bloomberg. Finally, we supplement the data by comparing them with data on ETF providers' homepages.

While Bloomberg has complete historical information on ETF prices, NAVs, index prices, shares outstanding, and trading volumes, ETF characteristics are supplemented by other available sources, because Bloomberg shows only a recent snapshot at the time of download. For instance, we obtain the ETF split information from the Center for Research in Security Prices (CRSP) and the expense ratio from the CRSP mutual fund database. In addition, we use Optionmetrics to infer that the ETF option is available after the first date observed in the data and consider the US Commodity Futures Trading Commission (CFTC) approval date of the ETF futures products as the starting date of the futures availability.[10] We extract ETF holding information from the Thomson 12D mutual fund holding data.

To investigate the effect of liquidity on the ETF returns and variances effectively, we exclude actively managed funds from the sample. Actively managed funds were first introduced in 2008. They are administered to achieve excess returns on the typical benchmark index by frequently buying or selling assets in the portfolio instead of passively following the index. As a result, actively managed funds are more likely to deviate from their underlying index returns, because their portfolio composition weights change frequently. Because the tracking errors of actively managed funds could be caused by management style, separating the effect of liquidity from the effect of management style on return and variance is difficult. Therefore, excluding actively managed funds from the sample is reasonable for an analysis of the liquidity effect on return and variance. As a result, the final sample contains only index-based passive ETFs. We exclude ETFs that do not contain enough information about the traded prices, NAV, or underlying index. Details about the sample construction procedure are included in Appendix A, Table A1. Our final sample consists of 1,307 US-listed ETFs.

We restrict the data after 2002 for two reasons. First, a sufficient number of ETFs to construct ten portfolios in Section 4 is not available before 2002. At the end of 2001, 101 ETFs were listed in the US market. Each portfolio could contain more than ten ETFs per year after 2001. Table 1 reports the annual breakdown of the sample by the number of funds initiated, delisted, and available at the end of the year, as well as the average market value, average trading volume, and average dollar trading volume. As seen in Table 1 and Fig. 1, the number of funds and trading volume increase sharply after the early 2000s, and the number of ETFs traded in the US increases to 1,239 by the end of 2012. Consequently, each portfolio in 2012 could have more than one hundred ETFs. Second, the minimum tick size of the bid-ask spread reduces from 1/16 to 1/100 in 2001. The change in the minimum tick size is related to the exogenous shock to the liquidity. Moreover, Fig. 1 shows a significant increase in the trading volume of the ETF market after 2002, although there was a decrease after the 2007–2009 financial crisis.[11] The increase in trading volume and the decrease in the bid-ask spread imply an important change in the liquidity measure. For these reasons, this study uses the data since 2002.

2.2. Liquidity measure

The daily individual ETF liquidity is measured using the daily relative effective spread calculated from the NYSE Trade and Quote (TAQ) database.[12] The daily relative effective half-spread is defined as the ratio of the effective half-spread to the trade price. The effective half-spread is defined as the absolute difference between the quote midpoint and the corresponding trade price, that is,

$$c_t^i = \frac{1}{n_t^i} \sum_{k=1}^{n_t^i} \frac{|p_{k,t}^i - m_{k,t}^i|}{p_{k,t}^i}, \tag{1}$$

where $p_{k,t}^i$ is the traded price, $m_{k,t}^i$ is the quote midpoint, and n_t^i is the number of trades at time k on day t for each security i. The relative effective spread is similar to the liquidity measure of "dollar cost per dollar invested" used in Acharya and Pedersen (2005, p. 386). They normalize the Amihud illiquidity measure so as to be similar to the cross-sectional mean and variance of the effective half-spread reported in Chalmers and Kadlec (1998). As a result, their liquidity measure is ultimately similar to the relative effective half-spread, which can be obtained directly from the TAQ data.

An advantage of using the TAQ data is that the spread variables can be observed on a daily basis. Examining the effect of liquidity on tracking errors is better using daily level measures than monthly-level measures because APs manage the ETF market through arbitrage activities, which

[9] Petajisto (2017) reports that the Bloomberg data cover up to 90% of all ETFs.

[10] For detailed information about CFTC-approved products, see https://www.cftc.gov/IndustryOversight/ContractsProducts/index.htm.

[11] In the middle of 2001, the NYSE began trading three unlisted ETFs (DIA, SPY, and QQQ) that are listed on the American Stock Exchange. Another 27 ETFs started to trade on the NYSE on April 15, 2002. Boehmer and Boehmer (2003) report that these events led to a large improvement in liquidity due to the competition for order flow among market centers.

[12] With the TAQ data, we identify the trading direction using the Lee and Ready (1991) algorithm. We also use various liquidity measures, such as effective spread, quoted half-spread, and relative quoted half-spread, to observe the effects of liquidity on tracking errors. All measures are computed from the TAQ data.

Table 1
Exchanged-traded fund (ETF) trends.
This table reports the annual breakdown of the sample by number of funds created, number of funds delisted, number of funds available at the end of year, average market value, average trading volume, and average dollar trading volume. This table also provides the market share of the top three (five and ten) ETFs in each year. The sample contains all the US ETFs that were listed on the US exchange during 1993–2012.

				Market value			Volume			Dollar volume		
Year	Created	Delisted	N	(Bill. $)	To3(%)	Top10(%)	(Mill. Sh)	To3(%)	Top10(%)	(Bill. $)	To3(%)	Top10(%)
1993	1	0	1	0.3	100.0	100.0	0.2	100.0	100.0	0.0	100.0	100.0
1994	0	0	1	0.5	100.0	100.0	0.4	100.0	100.0	0.0	100.0	100.0
1995	1	0	2	0.7	100.0	100.0	0.3	100.0	100.0	0.0	100.0	100.0
1996	17	0	19	1.7	91.3	97.0	1.2	85.0	94.3	0.1	96.4	98.7
1997	0	0	19	4.0	92.6	97.3	3.7	92.0	97.8	0.3	98.7	99.6
1998	10	0	29	10.0	87.8	94.6	9.9	85.5	96.7	0.9	97.5	99.3
1999	1	0	30	20.6	83.3	95.5	18.4	81.8	96.4	2.1	94.1	99.4
2000	50	0	80	46.4	76.8	90.4	42.1	87.2	94.8	4.2	93.3	97.7
2001	21	0	101	72.1	75.4	88.8	96.2	91.5	96.2	5.4	91.8	96.7
2002	15	3	113	91.3	62.1	80.3	147.7	88.3	94.1	7.3	88.9	94.7
2003	12	6	119	116.4	55.5	74.3	149.6	84.2	91.9	8.0	86.6	93.5
2004	35	0	154	176.4	43.3	65.9	192.7	76.9	89.5	11.6	79.3	90.7
2005	52	0	206	250.5	36.0	58.3	257.5	66.7	86.0	16.6	75.0	88.9
2006	157	1	362	355.9	29.5	50.7	369.1	60.8	80.7	24.4	69.3	85.3
2007	268	0	630	502.3	26.5	45.1	686.0	54.5	75.2	54.7	66.1	82.2
2008	162	50	742	556.8	25.1	41.8	1560.3	42.0	64.5	93.7	52.2	72.0
2009	127	51	818	608.8	21.9	39.6	1849.5	28.3	56.4	69.9	42.6	61.9
2010	180	48	950	839.3	19.6	38.0	1379.7	28.5	51.8	68.2	47.0	63.7
2011	231	15	1,166	1043.7	18.9	36.1	1357.6	27.8	49.5	77.5	46.7	62.3
2012	155	82	1,239	1203.7	18.9	35.8	952.6	27.1	46.3	56.2	46.7	61.5

Table 2
Summary statistics and correlations of exchange-traded fund (ETF) tracking errors.
This table provides the summary statistics and correlations of estimated tracking errors for ETFs from the inception date to the end of 2012 or the delisting date. Two tracking errors are defined. $\theta(Y-X)$ is the tracking error by taking the absolute value of the difference between one and the coefficient of X from the regression of Y on X. $\sigma(Y-X)$ is the standard deviation of the return difference between Y and X. The six tracking errors are estimated for each ETF using all daily returns. r_t, v_t, and f_t denote the daily ETF, net asset value (NAV), and index returns, respectively.

	Variable					
	$\sigma(r_t-f_t)$	$\sigma(v_t-f_t)$	$\sigma(r_t-v_t)$	$\theta(r_t-f_t)$	$\theta(v_t-f_t)$	$\theta(r_t-v_t)$
Panel A: Summary statistics for estimated tracking errors						
Mean	1.194%	0.419%	1.147%	15.846%	4.076%	16.470%
Std.Dev.	1.223%	0.952%	1.004%	17.680%	9.254%	17.615%
Panel B: Tracking error correlations for individual ETFs						
$\sigma(r_t-f_t)$	1.000					
$\sigma(v_t-f_t)$	0.712	1.000				
$\sigma(r_t-v_t)$	0.811	0.319	1.000			
$\theta(r_t-f_t)$	0.437	0.133	0.403	1.000		
$\theta(v_t-f_t)$	0.302	0.526	0.088	0.319	1.000	
$\theta(r_t-v_t)$	0.310	−0.008	0.447	0.808	0.093	1.000

affect tracking errors of ETFs on a daily basis. Moreover, the daily liquidity measure is suitable for the leveraged or inverse ETFs, because the use of the monthly measure can cause a mechanical difference between the monthly realized return and the monthly holding return (Cheng and Madhavan, 2009; Tang and Xu, 2013).

2.3. Tracking errors

To examine the effect of ETF liquidity on tracking errors, we examine the return differences between ETF and NAV, NAV and index, and ETF and index. We calculate annual tracking errors for the three kinds of return differences and construct daily tracking errors using the absolute value of return differences. For the annual panel data analysis, yearly tracking errors are defined using the following two methods. The first is regression analysis, in which the tracking error is defined as the absolute difference between one and the coefficient of the regression of two return series: ETF returns versus NAV returns(ETF-NAV), NAV returns versus index returns(NAV-index), or ETF returns versus index returns(ETF-index). The second is calculating the standard deviation of the return difference between the two return series.

Table 2 provides the summary statistics and averages of cross-sectional correlations of estimated yearly tracking errors for ETFs from the inception date to the end of the sample period or the delisting date. This table exhibits some interesting points about yearly ETF tracking errors. Panel A shows that NAV-index tracking errors are smaller than ETF-NAV or ETF-index tracking errors. This result implies that ETF returns are more likely to deviate from their index or NAV returns owing to various market factors that their managers cannot control. In addition, ETF-index tracking errors are similar to ETF-NAV tracking errors, suggesting that the former errors are explained by the latter errors.

Panel B shows that tracking errors from the regression are highly correlated with those calculated from standard deviations. This result implies that the two methods of computing tracking errors used in this study are fairly consistent and robust.

The correlations between ETF-NAV and NAV-index tracking errors are lower than the other correlations (0.319 for standard deviation tracking errors and 0.093 for regression tracking errors). This low correlation implies that some other factors (e.g., ETF market conditions) could be related to the ETF-NAV tracking errors, not the NAV-index tracking errors.

2.4. Threshold ETF data

When a stock is traded in the US market, the transaction should be settled three business days after the order is executed.[13] An FTD occurs when a market participant does not deliver the underlying security he or she sold or does not meet his or her contractual obligation. According to SEC Rule 203 of Regulation SHO, a stock is classified as a threshold stock if it has an aggregate FTD position over five consecutive settlement days with a registered clearing agency, with trading totaling ten thousand shares or more and amounting to at least 0.5% of the total outstanding shares of the issuer. The event of listing as a threshold stock can trigger a liquidity shock to the corresponding stock because of the regulatory enforcement to close out FTDs and to forbid naked shorting (Boni, 2006; Fotak et al., 2014). To explain the causal effects of liquidity on tracking errors, we use a threshold stock listing as an instrumental variable.

The SEC provides the FTD data on its website.[14] The SEC requires exchanges to publish a threshold list on a daily basis, and we acquire these lists from the various listing exchanges.[15] Threshold stocks are identified by CRSP Permnos after finding CUSIP codes in the FTD data by matching the ticker symbols of the FTD data with those of threshold data. Our data show that about 71.16% of ETFs are classified as a threshold stock at least once during the sample period.

3. The effect of ETF liquidity on tracking errors

No-arbitrage conditions imply that three daily return series (ETF, NAV, and index returns) must be identical owing to arbitrage activities of APs in a frictionless market. Fig. 4 shows that gaps exist among these return series. These return differences can be caused by various factors, such as trading activities, product structures, underlying securities markets, and ETF market conditions. A potential channel causing such return gaps is liquidity problems in the ETF market. Because the lack of liquidity in the ETF can lead to an increase in the cost of arbitrage activities of APs, it could prevent them from actively participating in the ETF market even if ETF prices deviate from their NAVs. This section investigates whether liquidity is related to ETF tracking errors by using panel regression analysis.

3.1. Arbitrage activity of authorized participants

In the ETF market, APs play an important role in keeping the series of ETF, NAV, and index returns close to each other. The return differences are typically removed by the arbitrage activity of APs. APs or market makers keep ETF prices in line with the values of their underlying portfolios by trading both ETFs and underlying securities simultaneously, that is, the so-called creation-redemption process. For instance, if an ETF price is lower (higher) than its NAV, then APs buy (sell) ETF shares and sell (buy) the basket of securities. If the current market price of an ETF becomes higher than its NAV, APs buy underlying securities to form a creation unit and deliver it to the ETF provider. After receiving the ETF shares from the ETF issuer, APs sell these ETF shares to the market.[16]

Arbitrage activity would be possible when APs are able to trade ETFs or underlying securities immediately and limitlessly. APs can get into trouble by constructing the basket of securities or by trading ETFs if ETFs or their underlying securities suffer from the lack of liquidity. Because each ETF has its own way of portfolio construction, the ETF provider could choose an appropriate method to replicate the underlying index return precisely.[17] Depending on the ETF prospectus, APs can borrow underlying securities or use derivatives to construct the basket of portfolios so that ETF portfolios (i.e., NAVs) can achieve the promised returns. Thus, many alternatives are available to tie the NAV returns to the underlying index returns. Depending on the market conditions, observed ETF prices are frequently different from their announced NAVs. In other words, the lack of liquidity or low trading volume in the ETF market could lead to a large price impact or the presence of stale prices, thereby causing a price gap between the ETF and its NAV. As a result, APs could bear unwanted costs related to borrowing underlying securities or holding inventories to manage the ETF market, if ETFs or underlying securities are not fully liquid. This situation implies that the lack of liquidity in the secondary market causes an increase in trading costs and ETF tracking errors.

[13] Since November 2017, it takes two days to reach settlement in the US. See details at https://www.sec.gov/news/press-release/2017-68-0.

[14] See https://www.sec.gov/data/foiadocsfailsdatahtm.

[15] Our final ETF stocks are listed on the NYSE Arca, NYSE MKT, or NASDAQ. Thus, we obtain the list of threshold stocks from those three exchanges websites. The link is https://www.sec.gov/investor/pubs/regsho.htm.

[16] Other types of arbitrage opportunities exist. For example, investors can use both S&P 500 futures contracts and the S&P 500 index-based ETFs to achieve arbitrage profits. Hasbrouck (2003) investigates the price discovery in the futures market and the ETF market and finds that most price discovery occurs in the former.

[17] There are broadly two paths of the creation and redemption process. For the in-kind method, APs create a basket of securities that are exchanged for ETF shares. For the cash method, which is allowed for some ETFs, APs deliver cash to the issuer and receive the ETF shares. Some ETFs use these two methods together to create shares.

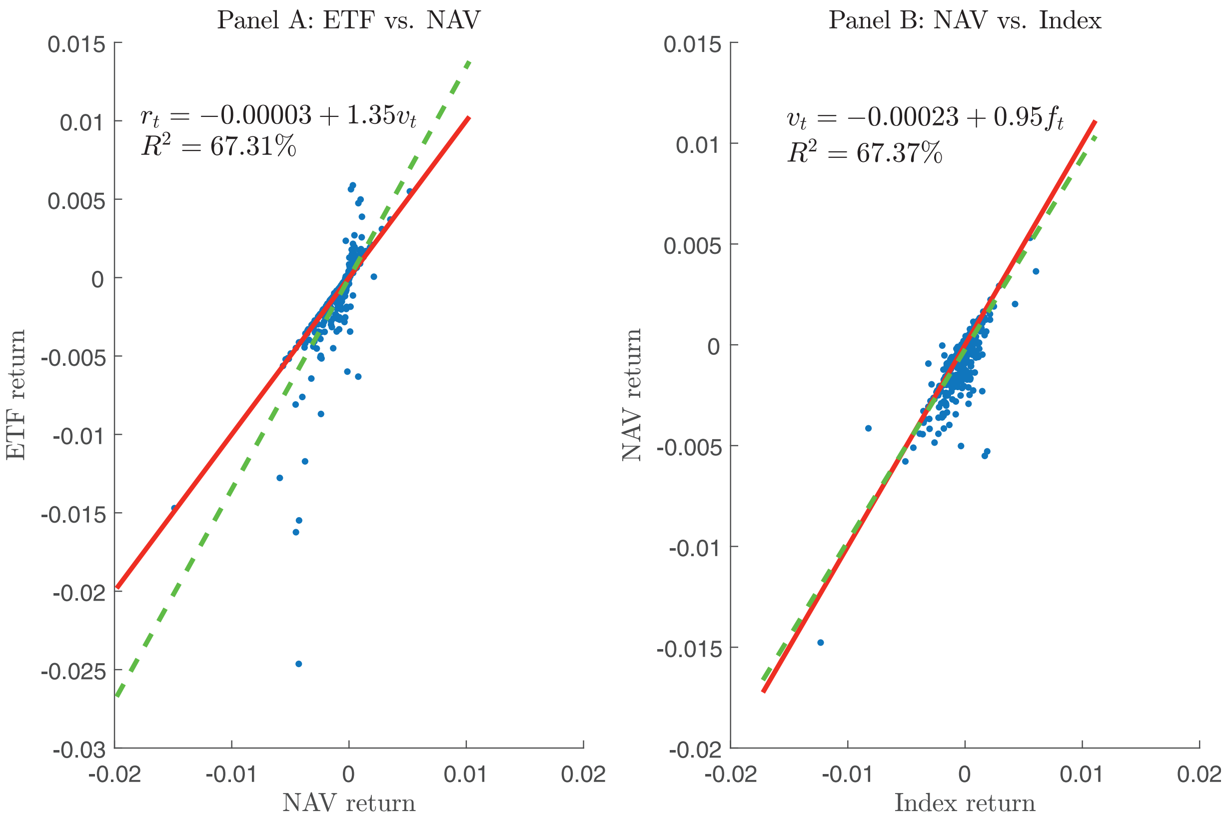

Fig. 4. Return distributions among exchange-traded fund (ETF), net asset value (NAV), and index returns. This figure illustrates cross-sectional relations between ETF returns and NAV returns (Panel A), and between NAV returns and underlying index returns (Panel B). Each point represents the time series average daily return series for the entire sample period. The solid line represents the fitted regression line and the dotted line is the forty five degree line.

3.2. ETF illiquidity and tracking errors

Fig. 4 shows the cross-sectional relations between ETF and NAV returns (Panel A) and between NAV and index returns (Panel B). Each point represents the time series average daily return of each ETF from the inception date to the end of 2012 or the delisting date. The solid lines indicate the fitted regression lines between two return series, and the dotted lines are the 45-degree lines. In Panel B, most US ETFs appear to be managed correctly to track their underlying indexes, although some ETFs are shown to have large tracking errors. The coefficient of the NAV-index cross-sectional regression is 0.95, which is close to one, suggesting that US ETFs are managed to track their underlying indexes precisely. Panel A shows that there are relatively large tracking errors between ETFs and their NAVs. The fitted coefficient of the ETF-NAV regression is 1.35, implying that ETF returns deviate from NAV returns more frequently than NAV returns do from index returns. Thus, Fig. 4 suggests that ETF returns can deviate from NAV returns even if ETF portfolios are managed precisely to mimic their underlying indexes.

Figs. 5 and 6 provide the same illustrations for individual ETFs. Fig. 5 shows the return relations for SPDR S&P 500 ETF Trust (SPY), and Fig. 6 shows those for iShares MSCI Emerging Markets Index (EEM). Both ETFs are very liquid in US markets. Incepted in 1993, the SPY, the oldest and the largest ETF in the US, tracks the performance of the S&P 500 index. In Fig. 5, the fitted coefficient of the ETF-NAV regression is 0.96 with $R^2 = 91.84\%$ and that of the NAV-index regression is 1.00 with $R^2 = 96.34\%$. These results suggest that the SPY tracks the S&P 500 index correctly, and its market prices are formed close to its NAVs.

The EEM in Fig. 6 appears to have relatively larger tracking errors than the SPY does.[18] The EEM, one of the most popular international ETFs in the US, is designed to track the performance of the MSCI emerging market index. Because the EEM physically holds emerging market stocks, EEM market prices could fail to reflect the changes in the underlying index immediately. Although the EEM is managed correctly to track the underlying index ($R^2 = 84.11\%$ and the coefficient is 1.01), its market prices are shown to deviate more frequently from its NAVs ($R^2 = 70.51\%$ and the coefficient is 1.18). In summary, both figures suggest that tracking errors in the ETF-NAV returns are more severe than those in the NAV-index returns.

[18] In 2012, the average daily trading volume for the SPY was 143 million shares and that for the EEM was 49 million shares. The average daily relative bid-ask spread for SPY was 0.010% and that for the EEM was 0.016%. The average daily turnover for the SPY was 18.96% and that for the EEM was 5.46%. By comparison, the average daily trading volume was 0.93 million shares, the average daily relative bid-ask spread was 0.014%, and the average daily turnover was 3.79% for all ETFs in 2012.

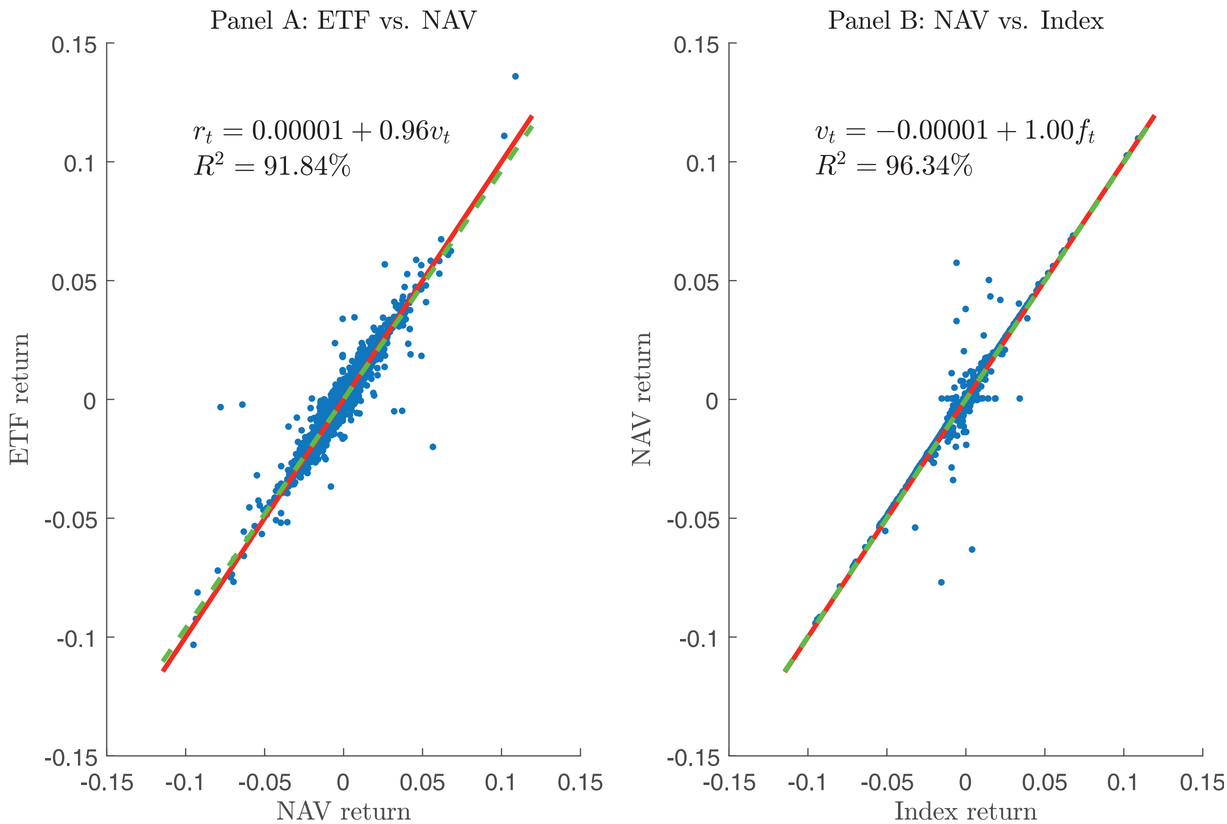

Fig. 5. Return distributions among exchange-traded fund (ETF), net asset value (NAV), and index returns: SPY. This figure illustrates ETF, NAV, and index returns of SPY, which is SPDR S&P 500 ETF issued by State Street Global Advisors. Panel A depicts the relation between daily ETF and NAV returns, and Panel B depicts the relation between daily NAV and index returns, from January 22, 1993 to December 31, 2012. The solid line represents the fitted regression line and the dotted line is the forty five degree line.

The time series relations between return differences and illiquidity are illustrated in Fig. 7. The first line depicts the averages of the daily relative bid-ask spread. The bottom two lines are the average absolute daily return differences between ETFs and NAVs and between NAVs and indexes. Both return differences and illiquidity co-move over time. In other words, common factors appear to affect both illiquidity and return differences. The ETF-NAV return differences are generally higher than NAV-index return differences over the sample period. Both ETF market illiquidity and tracking errors increase during the financial crisis period after 2008, suggesting that the illiquidity measure reflects the recent liquidity crisis well.

3.3. Panel regression

Fig. 7 intuitively shows the relations between ETF illiquidity and the ETF's tracking errors. This section formally tests the effect of ETF illiquidity on tracking errors using panel regressions. To this end, we estimate illiquidity and tracking errors at the daily or yearly frequency to investigate their relations.

Three types of tracking errors are used to investigate the effect of liquidity on tracking errors: ETFs versus NAVs, ETFs versus indexes, and NAVs versus indexes. We use two types of yearly tracking errors to investigate the effect of liquidity on tracking errors. The main variable of interest is illiquidity, which is defined as the relative effective half-spread. Thus, high values of relative spread imply low liquidity.

ETF prices are affected by both product structures and ETF market conditions. Tracking errors could exist when the ETF market is illiquid although the underlying portfolios are constructed to track the underlying index correctly and perfectly. The tracking errors could be affected by ETF structures, as well as by the ETF trading activity. For instance, ETFs replicating the US market indexes are less likely to deviate from the underlying indexes than ETFs investing in other countries. Furthermore, the NAV-index tracking error could be caused by the replication methods, such as holding underlying securities directly or creating the return using either futures or swaps. We include various control variables to capture both market conditions and fund characteristics.

Controlling for ETF market conditions, we include AUM, dollar trading volume, underlying index return volatility, shares outstanding, and volatility of share growth. If the underlying index return is very volatile, the ETF price perhaps does not reflect the underlying index movement promptly, because the market makers or investors need to trade the ETFs more frequently. The annual underlying index return volatility is added to control this effect.

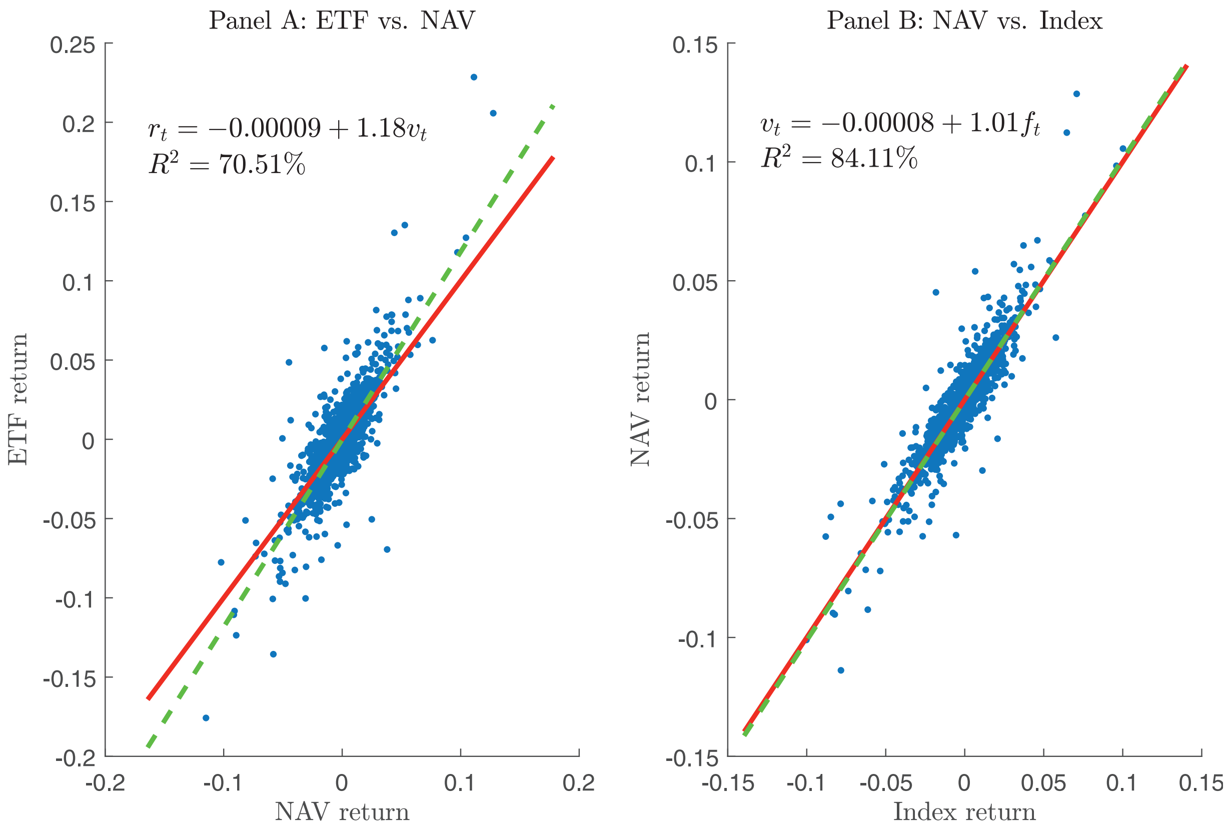

Fig. 6. Return distributions among exchange-traded fund (ETF), net asset value (NAV), and index returns: EEM. This figure illustrates ETF, NAV, and index returns of EEM, which is iShares MSCI Emerging Market Index ETF issued by iShares. Panel A depicts the relation between daily ETF and NAV returns, and Panel B depicts the relation between daily NAV and index returns, from April 11, 2003 to December 31, 2012. The solid line represents the fitted regression line and the dotted line is the forty five degree line.

Moreover, the log of the average annual dollar trading volume is included in the regressions. The ETFs with large dollar trading volume could cause a tracking error, because heavy trading volume is related to unnecessary price pressure. We include the number of shares or the AUM to represent the size of the ETF or cash flows into funds. The shares' growth volatility indicates how the ETF is actively traded in the market. A frequent change in outstanding shares implies active management by APs to manage tracking errors or volatile fund flows. To control these effects, we include the logarithm of the average number of shares and the standard deviation of the share growth rate during the year.

Aside from the variables associated with market conditions, we include the ETF characteristics to capture additional effects caused by fund structures. These are US-based: whether the underlying securities in the ETF baskets invested in US assets; derivatives based: whether the ETF uses derivatives to replicate the underlying index return; swap based: whether the ETF uses swaps to replicate the underlying index return; futures available: whether the ETF has futures contracts based on it; options available: whether the ETF has option contracts based on it; leveraged funds: whether the ETF is leveraged or inverse; expense ratio: the annual expense ratio of the ETF; in-kind: whether the ETF is replicated physically; and optimized: whether the ETF is replicated by optimizing the basket of securities.

3.4. Panel regression results

This section reports the yearly and daily panel regression results.

3.4.1. Yearly panel regression

Table 3 reports results from the pooled panel regressions of yearly tracking errors on the ETF illiquidity measure and other control variables. The tracking errors are calculated by taking the absolute value of the difference between one and the regression coefficient, which is estimated from regressing one return series on another return series for each ETF every year. From left to right, the dependent variable in each column represents the tracking error between the ETF and the index (Columns 1 and 4), the ETF and the NAV (Columns 2 and 5), and the NAV and the index (Columns 3 and 6). Because market liquidity is heavily affected when markets are in turmoil, we provide additional tests after excluding the financial crisis period from Columns 4 to 6. All regression specifications include year fixed effects, and standard errors are double-clustered at the fund and year level.

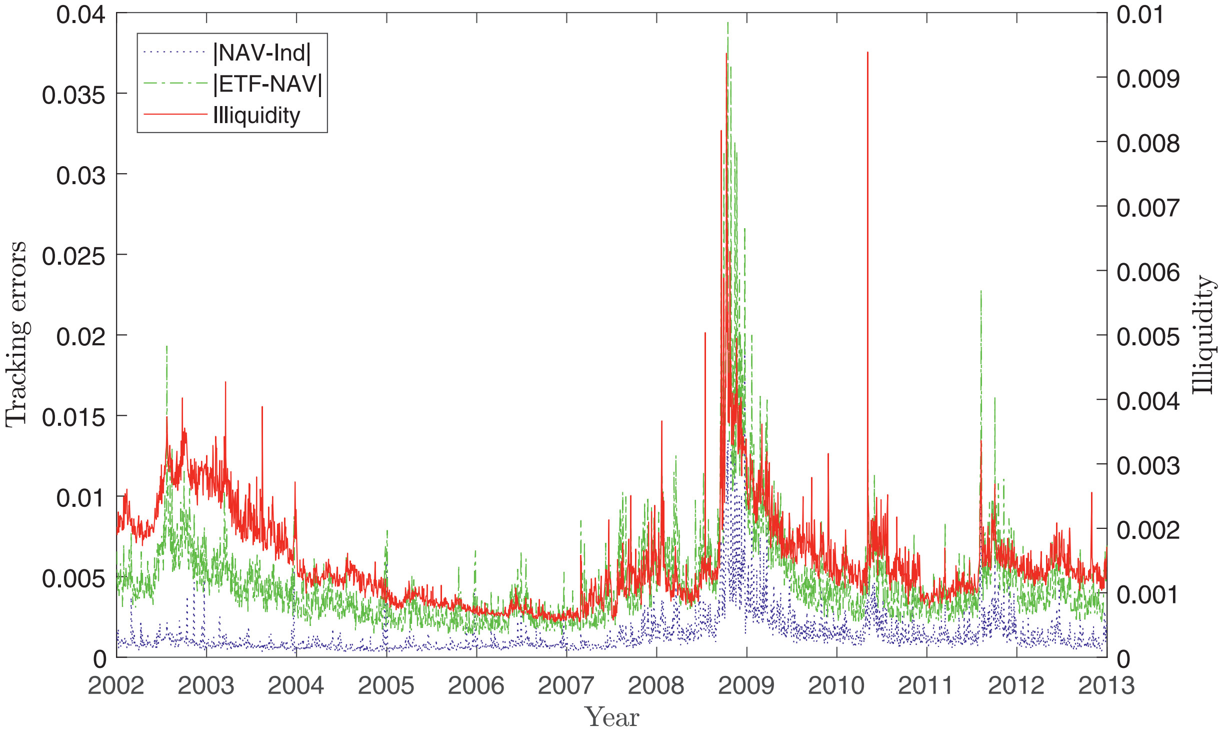

Fig. 7. Daily time series for illiquidity and return differences. This figure illustrates historical time series of illiquidity and absolute values of return differences from 2002 to 2012. The solid line is the average illiquidity, which is the cross-sectional average of daily relative effective spreads of all US exchange-traded funds (ETFs). The dotted line is the average absolute values of return differences between net asset value (NAV) and index returns, the dashed line is the average absolute value of return differences between ETF and NAV returns.

Columns 1 and 2 show that the coefficients on average illiquidity are positive and significant. These results suggest that illiquid ETFs are more likely to deviate from their NAVs or underlying index returns. The coefficient of 13.038 indicates that if an ETF's average relative spread increases by 1%, then the tracking error in ETF-index return increases by about 13% while holding other characteristics constant. This illiquidity measure similarly affects the ETF-NAV tracking error (Column 2). Both magnitudes of coefficients on illiquidity are similar (13.038 and 12.938), implying that most tracking errors are likely to occur between ETF returns and NAV returns. The results in Columns 3 and 6 (NAV-index tracking error) show that ETF illiquidity is not associated with the tracking error between NAV and underlying index returns. In other words, ETF market conditions do not account for the tracking error between NAV and index returns.

Large trading volume does not seem to widen the ETF tracking errors. Heavy trading volume can increase the efficiency of the asset price, because large trading volume indicates the presence of informed traders (Karpoff, 1987). The results show that the coefficients on dollar trading volume are positive for the ETF-index or ETF-NAV tracking errors, but negative for the NAV-index tracking errors, albeit insignificantly. The effect is significant only for the ETF-NAV tracking errors. The coefficients on Log(AUM) and Log(Shares Outstanding), which are proxies for fund size, are negative, but not significant, across all tracking errors. These results offer weak evidence that large funds tend to have smaller tracking errors.

The coefficients on the share growth volatility are negative and significant for the ETF-NAV or ETF-index tracking errors. The share growth volatility is measured as the standard deviation of the shares' growth rate. Large share growth volatility implies that creation and redemption processes occur frequently. Thus, the high volatility in the shares' growth rate implies that ETFs are attractive in the market. Alternatively, the frequent adjustment share of the ETF can be interpreted as active management of APs to reduce the tracking error between the ETF and the NAV, or the underlying index.

Regarding the fund characteristics, small tracking errors are observed when the underlying securities in the ETF baskets invest in US assets or when options are available for the ETF. Consistent with previous studies, ETFs replicating the US-based indexes tend to have small tracking errors.[19] This finding is not surprising given that the US market is one of the most liquid markets in the world traders can trade both ETF and underlying securities without a time lag. In addition, equity-type ETFs tend to have smaller tracking errors than non-equity ETFs do. This result implies that the arbitrage activity of APs for equity-type ETFs can easily manage portfolios, because equity markets are more liquid than other types of asset markets.

[19] Engle and Sarkar (2006) investigate premiums (discounts), which are the same as ETF-NAV tracking errors, for 21 domestic and 16 international ETFs. They find that the tracking errors for domestic ETFs are generally small and temporary, but those for international ETFs are large and persistent.

Table 3
Exchange-traded fund (ETF) illiquidity and tracking errors: regression-based tracking errors.

This table reports coefficients estimates of yearly regressions of ETF tracking errors on ETF illiquidity. The dependent variables are annual tracking errors, calculated by taking the absolute difference between one and regression coefficients of ETF returns on its index returns (Columns 1 and 4), of ETF returns on net asset value (NAV) returns (Columns 2 and 5), or of NAV returns on index returns (Columns 3 and 6). Columns 1–3 show the estimation results for the whole sample period; Columns 4–6 for the financial crisis period. The main independent variable is annual average of daily relative effective spread (ETF illiquidity) computed from the NYSE Trade and Quote (TAQ) database. All independent variables are yearly averages of daily variables. All daily variables are defined in Appendix B. All regressions include year fixed effects. t-statistics based on standard errors double-clustered at the fund and year level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	All sample			Financial crisis period		
Variable	θ(ETF-IND) (1)	θ(ETF-NAV) (2)	θ(NAV-IND) (3)	θ(ETF-IND) (4)	θ(ETF-NAV) (5)	θ(NAV-IND) (6)
ETF Illiquidity	13.038**	12.938**	−0.777	15.818**	16.540**	−1.795
	(2.42)	(2.38)	(−0.62)	(2.91)	(3.15)	(−1.71)
Log(AUM)	−1.483	−0.787	0.337	−1.136	−0.444	−0.063
	(−1.59)	(−0.85)	(0.69)	(−1.23)	(−0.48)	(−0.17)
Log(Dollar Trading Volume)	0.621	0.872*	−0.236	0.734	1.068*	−0.035
	(0.95)	(1.88)	(−0.98)	(0.95)	(2.11)	(−0.17)
Index Volatility	−0.068	−1.006*	0.808	0.145	−0.803	−0.076
	(−0.11)	(−2.03)	(1.22)	(0.20)	(−1.23)	(−0.19)
Log(Shares Outstanding)	0.204	−0.830	−0.637	0.041	−0.824	−0.432
	(0.21)	(−0.94)	(−1.42)	(0.04)	(−0.96)	(−1.22)
Shares Volatility	−24.290*	−22.446**	4.821	−23.295	−15.881*	2.995
	(−2.19)	(−3.07)	(1.65)	(−1.58)	(−1.86)	(0.78)
Equity-Type ETF	−12.866***	−14.187***	−6.113***	−14.492***	−16.073***	−4.966***
	(−4.00)	(−5.21)	(−4.82)	(−4.63)	(−6.80)	(−5.10)
Invested in US Assets	−3.971**	−2.603*	−4.242***	−4.062**	−2.699*	−3.841***
	(−3.04)	(−2.14)	(−5.61)	(−2.91)	(−2.02)	(−5.39)
Swap Based	10.782*	3.873	9.048*	11.579**	6.631*	8.428*
	(2.12)	(0.90)	(2.09)	(2.60)	(1.90)	(2.22)
Derivatives Based	−9.518**	−11.912**	−2.130	−9.598**	−11.888**	−2.138
	(−2.67)	(−2.92)	(−1.43)	(−2.50)	(−3.13)	(−1.79)
Leveraged Fund	−4.465	2.327	−7.212	−3.716	0.586	−4.777
	(−0.77)	(0.84)	(−1.27)	(−0.77)	(0.30)	(−0.97)
Futures Available	0.547	0.868	0.241	−0.579	−1.010	0.120
	(0.44)	(0.60)	(0.54)	(−0.50)	(−1.04)	(0.21)
Options Available	−2.688**	−3.160**	0.780	−2.373*	−2.573**	0.733
	(−2.68)	(−2.85)	(1.65)	(−2.16)	(−2.31)	(1.70)
In-Kind	0.423	0.202	−0.720	1.137	1.405	−0.621
	(0.34)	(0.15)	(−1.09)	(0.89)	(1.34)	(−0.94)
Optimized	0.239	1.558	−1.177*	0.084	1.367	−0.926
	(0.25)	(1.46)	(−1.97)	(0.09)	(1.35)	(−1.49)
Expense Ratio	1.354	2.139	0.299	−0.267	1.073	0.428
	(0.74)	(1.67)	(0.22)	(−0.13)	(0.61)	(0.28)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	5,471	5,484	5,611	4,378	4,379	4,488
Adjusted R^2	0.092	0.206	0.109	0.086	0.214	0.099

With different specifications of tracking errors, Table 4 again confirms the results in Table 3. The dependent variables used in Table 4 are the yearly standard deviation of daily return differences between the ETF and index (Columns 1 and 4), between the ETF and the NAV (Columns 2 and 5), and between the NAV and index (Columns 3 and 6). The results are very similar under the alternative tracking error measure. The coefficients on illiquidity are still positive and significant for the ETF-index and ETF-NAV tracking errors. Moreover, ETFs investing in US assets or equity-based ETFs tend to have small tracking errors. One different feature is that the coefficients on index return volatility are positive and significant, suggesting that APs can have trouble tracking underlying indexes or constructing portfolios when underlying indexes are volatile.

Overall, ETF tracking errors are severe when ETFs are not actively traded in the market. One potential benefit of investing in ETFs is that investors can avoid high transaction costs when ETFs track inaccessible markets or assets that are difficult to track. Illiquid ETFs could be riskier investments than investing directly in underlying assets owing to the high tracking errors. In these situations, investors can face another type of risk, namely, tracking error risk caused by the lack of liquidity in secondary markets. Investing in illiquid ETFs with severe tracking errors could offset the benefits of ETF investments.

3.4.2. Daily panel regression

Although the yearly panel regression clearly demonstrates the relations between ETF illiquidity and ETF tracking errors, the effect of liquidity on tracking errors is likely to occur for a very short time. In general, APs maintain the ETF and its portfolio on a daily basis and continue to attempt to reduce any difference between the two returns through immediate arbitrage activities.

Table 4
Exchange-traded fund (ETF) illiquidity and tracking errors: standard deviation–based tracking errors.
This table reports coefficients estimates of yearly regressions of ETF tracking errors on ETF illiquidity. The dependent variables are annual tracking errors, calculated by taking the standard deviation of differences between ETF returns and index returns (Columns 1 and 4), between ETF returns and net asset value (NAV) returns (Columns 2 and 5), or between NAV returns and index returns (Columns 3 and 6). Columns 1–3 show the estimation results for the whole sample period; Columns 4–6 for the financial crisis period. The main independent variable is annual average of daily relative effective spread (ETF Illiquidity) computed from the NYSE Trade and Quote (TAQ) database. All independent variables are yearly averages of daily variables. All daily variables are defined in Appendix B. All regressions include year fixed effects. t-statistics based on standard errors double-clustered at the fund and year level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	All sample			Financial crisis period		
Variable	σ(ETF-IND) (1)	σ(ETF-NAV) (2)	σ(NAV-IND) (3)	σ(ETF-IND) (4)	σ(ETF-NAV) (5)	σ(NAV-IND) (6)
ETF Illiquidity	0.014***	0.015***	0.001	0.014***	0.015***	−0.000
	(12.67)	(13.79)	(0.98)	(11.88)	(13.65)	(−0.65)
Log(AUM)	0.001	0.001	0.002	0.000	0.000	0.000
	(0.87)	(1.13)	(1.33)	(0.30)	(0.60)	(0.72)
Log(Dollar Trading Volume)	−0.000	−0.000	−0.001	−0.000	−0.000	−0.000
	(−1.46)	(−1.16)	(−1.55)	(−1.06)	(−0.28)	(−1.35)
Index Volatility	0.003***	0.002***	0.004**	0.003***	0.002***	0.001***
	(6.95)	(4.92)	(2.43)	(6.09)	(5.13)	(5.91)
Log(Shares Outstanding)	−0.001	−0.001	−0.001	−0.000	−0.000	−0.000
	(−1.11)	(−1.46)	(−1.39)	(−0.78)	(−1.31)	(−1.13)
Shares Volatility	0.000	−0.001	0.005	−0.000	−0.000	0.002
	(0.06)	(−0.98)	(1.79)	(−0.07)	(−0.27)	(1.49)
Equity-Type ETF	−0.002*	−0.001*	−0.002*	−0.002*	−0.001	−0.001
	(−1.91)	(−1.89)	(−2.10)	(−1.89)	(−1.68)	(−1.79)
Invested in US Assets	−0.005***	−0.003***	−0.004***	−0.005***	−0.003***	−0.004***
	(−5.64)	(−5.73)	(−5.28)	(−5.29)	(−5.43)	(−5.35)
Swap Based	0.001	−0.004	0.005*	0.003	−0.000	0.006**
	(0.18)	(−1.12)	(2.15)	(1.50)	(−0.41)	(2.91)
Derivatives Based	−0.002	−0.003	−0.001	−0.000	−0.001	−0.000
	(−0.82)	(−1.31)	(−0.85)	(−0.19)	(−0.78)	(−0.26)
Leveraged Fund	−0.000	0.003	−0.004	−0.003	−0.002	−0.003
	(−0.08)	(0.66)	(−1.54)	(−1.25)	(−1.80)	(−1.13)
Futures Available	0.001	0.001	0.000	−0.000	0.000	−0.000
	(0.89)	(1.15)	(0.36)	(−0.10)	(0.17)	(−1.00)
Options Available	−0.001**	−0.002***	0.000	−0.001	−0.001***	0.001**
	(−2.40)	(−3.40)	(0.85)	(−1.77)	(−3.91)	(2.67)
In-Kind	−0.001*	−0.001	−0.001*	−0.001	−0.000	−0.000
	(−1.88)	(−1.66)	(−1.83)	(−1.45)	(−1.18)	(−1.42)
Optimized	−0.000	0.000	−0.001**	−0.000	0.000	−0.001**
	(−0.90)	(0.82)	(−2.55)	(−1.14)	(0.77)	(−2.41)
Expense Ratio	0.002	0.003**	−0.001	0.000	0.001*	−0.001
	(1.29)	(2.62)	(−1.78)	(0.12)	(1.95)	(−1.44)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	5,471	5,484	5,611	4,378	4,379	4,488
Adjusted R^2	0.532	0.500	0.322	0.511	0.485	0.286

In other words, investigating the relations could be more desirable using daily data instead of yearly data, because arbitrage opportunities are very short-lived and immediate. Therefore, we investigate the effect of liquidity on ETF tracking errors more precisely by using daily panel data.

We define daily tracking errors, the key variable in the analysis of daily data, as the absolute value of the difference between the two returns. For consistency with the previous analysis, we include most of the control variables used in the yearly panel and add intraday volatility and normalized absolute order imbalance. Daily fixed effects are included, and standard errors are double-clustered at the fund and day level. The first three columns in Table 5 report the results for pooled daily panel regressions. As with previous yearly panel results, the coefficients of illiquidity are still positive and significant. Our claim that illiquidity is positively related to tracking errors still holds at the daily level. Finally, other control variables show similar patterns with yearly data analysis.

The results from Tables 3, 4, and 5 imply that liquidity is an important factor in determining the tracking error between the ETF and its NAV or its index at both the daily and the yearly level. Nevertheless, the causal relation between ETF liquidity and tracking errors needs to be examined more closely, because both could be determined by the strategic investment behavior of APs or investors. To explain the causal structure between the two, we explore the relations by employing an instrumental variable that affects liquidity but does not affect tracking error innovations.

3.5. Instrumental variable regression: Reg SHO threshold flag

The results of the panel regressions in Section 3.4 perhaps do not lead to a causal interpretation that ETF illiquidity increases tracking errors. If an unobserved factor affects both ETF liquidity and tracking errors, liquidity simply could be correlated with tracking errors. Furthermore,

Table 5
Exchange-traded fund (ETF) illiquidity and tracking errors: instrumental variable approach.
This table reports coefficients estimates of daily regressions of ETF tracking errors on ETF illiquidity. The dependent variables are daily tracking errors, calculated by taking the absolute values of daily return differences between ETF and its index (Columns 1 and 4), between ETF and its net asset value(NAV) (Columns 2 and 5), or between NAV and its index (Columns 3 and 6). Columns 1–3 are pooled ordinary least square estimation results; Columns 4–6, two-stage regression results by employing an instrumental variable. The instrumental variable is an indicator variable if an ETF receives a threshold flag. The first day of the threshold flag as the indicator value is one if the ETF receives the threshold flag on consecutive days. The main independent variable is the daily relative effective spread (ETF Illiquidity) computed from the NYSE Trade and Quote (TAQ) database. All other daily variables are defined in Appendix B. All regressions include day fixed effects. t-statistics based on standard errors double-clustered at the fund and day level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Panel regression			Instrumental variable regression		
Variable	|ETF-IND| (1)	|ETF-NAV| (2)	|NAV-IND| (3)	|ETF-IND| (4)	|NAV-IND| (5)	|ETF-NAV| (6)
ETF Illiquidity	0.453***	0.541***	0.025	3.529***	4.581***	−0.368
	(11.43)	(12.42)	(0.95)	(2.98)	(3.76)	(−0.50)
Log(AUM)	−0.001***	−0.001***	−0.000	0.001	0.002**	−0.000
	(−4.40)	(−3.50)	(−0.32)	(1.22)	(2.26)	(−0.61)
Log(Dollar Trading Volume)	0.001***	0.001***	0.000**	0.000***	0.000**	0.000**
	(5.92)	(6.30)	(2.29)	(3.23)	(2.50)	(2.46)
Absolute Order Imbalance	−0.000	−0.000	0.000	−0.000**	−0.000**	0.000
	(−1.51)	(−1.12)	(0.49)	(−2.24)	(−2.07)	(0.68)
Intraday Volatility	0.000***	0.000***	0.000*	−0.001	−0.001**	0.000
	(3.81)	(4.19)	(1.96)	(−1.59)	(−2.20)	(0.91)
Shares Outstanding Growth	0.001***	0.000	0.001***	0.001**	0.000	0.001***
	(2.63)	(0.04)	(3.47)	(2.13)	(0.11)	(3.47)
Log(Shares Outstanding)	0.000**	0.000	−0.000*	−0.000	−0.001*	−0.000
	(2.05)	(1.36)	(−1.80)	(−0.66)	(−1.80)	(−0.84)
Equity-Type ETF	−0.000	−0.001	−0.000	0.000	0.001	−0.000
	(−0.56)	(−0.98)	(−0.58)	(0.62)	(0.81)	(−0.76)
Invested in US Assets	−0.005***	−0.003***	−0.003***	−0.003***	−0.000	−0.003***
	(−13.10)	(−13.15)	(−7.77)	(−2.80)	(−0.13)	(−4.99)
Swap Based	0.002	−0.001	0.004*	0.003	−0.000	0.004
	(0.89)	(−1.01)	(1.68)	(1.24)	(−0.23)	(1.62)
Derivatives Based	−0.001	−0.002	0.000	0.001	−0.000	0.000
	(−0.48)	(−1.61)	(0.59)	(0.52)	(−0.18)	(0.38)
Leveraged Fund	0.000	0.001	−0.001	0.000	0.001	−0.001
	(0.14)	(1.64)	(−0.36)	(0.14)	(1.29)	(−0.36)
Futures Available	−0.001*	−0.000	−0.000	−0.001***	−0.001**	−0.000
	(−1.87)	(−0.70)	(−1.29)	(−2.90)	(−2.55)	(−0.67)
Options Available	−0.000	−0.001***	0.001***	0.001*	0.001	0.001**
	(−1.39)	(−5.12)	(4.09)	(1.68)	(1.32)	(1.97)
In-Kind	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(−1.13)	(−0.95)	(−1.55)	(−0.78)	(−0.58)	(−1.54)
Optimized	0.000	0.001***	−0.001***	0.001*	0.001***	−0.001***
	(0.53)	(3.01)	(−4.23)	(1.82)	(3.64)	(−3.58)
Expense Ratio	0.002***	0.003***	−0.000	0.001	0.002***	−0.000
	(2.69)	(5.66)	(−0.69)	(1.62)	(3.12)	(−0.56)
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,113,226	1,155,597	1,113,376	1,113,226	1,155,597	1,113,376
Adjusted R^2	0.254	0.219	0.109	−0.126	−0.536	0.097

large tracking errors could discourage investors from trading ETFs, thereby any reducing liquidity provision. This section addresses the underlying causal structures between ETF liquidity and the ETF tracking errors by exploiting exogenous liquidity shocks generated by threshold securities flags. The identifying assumption is that receiving a threshold security flag is an exogenous event relative to the ETF tracking errors.

The FTD is a situation in which a market participant does not deliver the underlying security he or she sold at the time of settlement. Evans et al. (2017) report that ETFs account for a significant portion of FTDs in the US stock markets. They argue that market makers or APs can strategically decide FTDs to reduce transaction costs when a demand shock occurs in the ETF security. These strategic FTDs are particularly effective for ETFs with high creation fees or illiquid underlying basket securities.[20] Previous studies also provide empirical evidence that FTDs encourage APs to provide more liquidity and employ effective arbitrage activities (Battalio and Schultz, 2011; Fotak et al., 2014; Stratmann and Welborn, 2016).[21] Strategic FTDs enable APs to delay the creation process after they sell new ETF shares to meet large order imbalances.

[20] For example, APs can create and redeem ETFs in certain units, such as 50,000 shares or 100,000 shares, with fees. If the created units are less than market demand, APs must keep them in inventory. APs have an incentive to minimize the frequency of the creation and redemption process for reducing costs and managing inventory risks.

[21] Fotak et al. (2014) argue that FTDs can encourage market participants to provide liquidity and be involved in useful arbitrage activities. Battalio and Schultz (2011) and Stratmann and Welborn (2016) support their view.

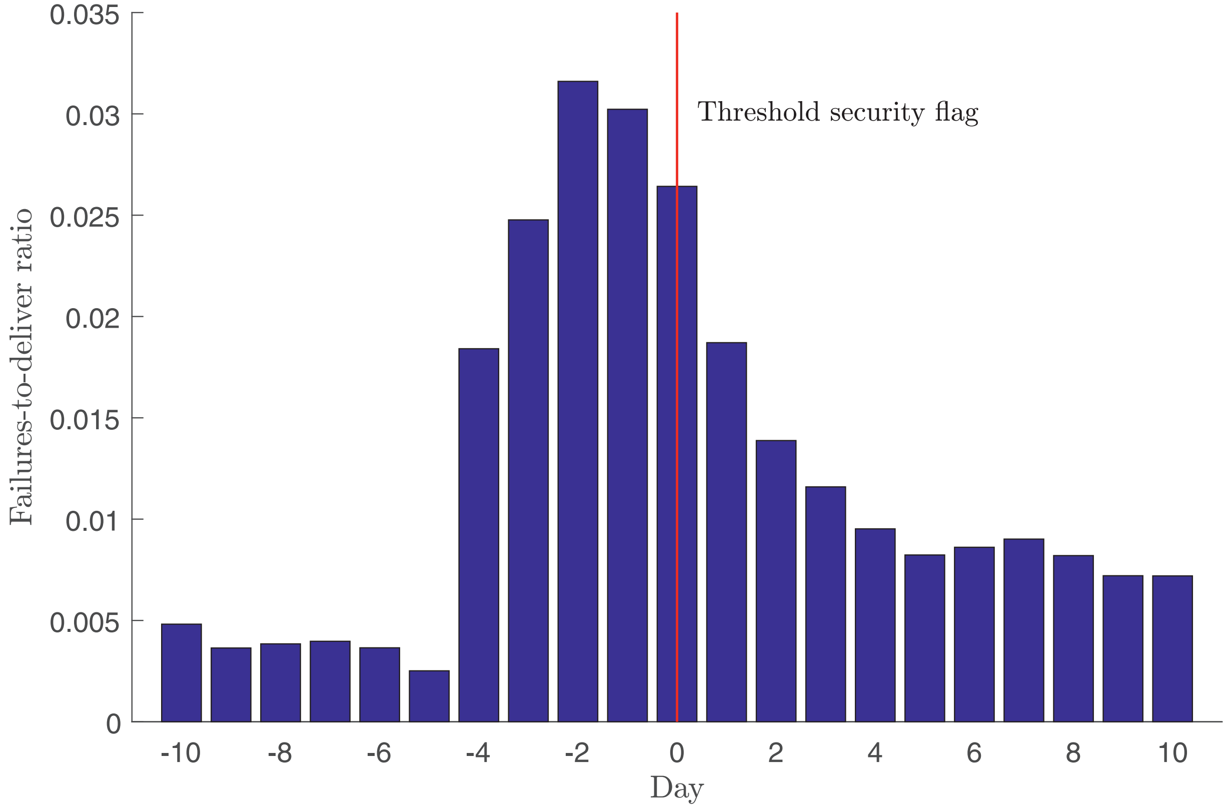

Fig. 8. Failures-to-deliver (FTD) ratio around the day as listed as threshold stocks. This figure illustrates the FTD ratio around the first day when an exchange-traded fund (ETF) is assigned as the threshold stocks. Day 0 denotes the first day of receiving the threshold of the ETFs. The FTD ratio is the number of outstanding failed positions reported on day $t + 3$ divided by the total number of shares outstanding on day t of the ETF. The bar denotes the value-weighted average of FTD ratios.

Despite the potential benefits of market making, the SEC regulates large and persistent FTDs. The SEC Rule 203 of Reg SHO requires listing exchanges to classify a stock as a threshold stock if large FTDs occur for five consecutive settlement days.[22] When a security receives a threshold flag, it becomes subject to the mandatory close-out requirement and the pre-borrowing requirement. APs must immediately close out of unsettled positions if FTDs persist for 13 consecutive settlement days. Despite these requirements, FTDs still increase before the amendment of the SEC rule in 2009. In 2009, SEC Rule 204 required the reduction of its mandatory close-out requirement to four days for general traders and six days for market makers.[23] Until all FTDs that need to be delivered immediately are closed, APs cannot short sell threshold securities without borrowing.

Such regulatory restrictions can result in exogenous liquidity shocks once ETFs receive a threshold flag. APs can strategically fail to deliver certain ETFs for saving creation or redemption fees. However, endogenous actions of APs perhaps do not apply to threshold securities, which force the regulatory enforcement of immediate close-out and pre-borrowing requirements and, thus, can increase their operating costs. For example, an AP can short sell new ETFs to meet order imbalances without borrowing or creating shares, but it could strategically fail to deliver ETF securities to save the costs. If the security is classified as a threshold security, APs must create or purchase additional ETF shares to close out failed positions because such strategic FTDs are impossible. The efforts of APs to resolve failed positions could lead to additional transactions or an increase in the number of ETF shares, which, in turn, could increase ETF liquidity. Therefore, a threshold security flag would be a valid instrument that is associated with liquidity changes.

According to Fig. 8, FTDs increase sharply before a threshold flag. This rapid increase is driven by sudden buying pressure or the strategic delay of ETF creation by APs. After a threshold flag, FTDs sharply decrease. This sharp decline is due to the close-out and pre-borrowing requirements imposed by Rule 203(b)(3) of Regulation SHO. These two regulatory requirements bring about exogenous changes in ETF market liquidity, which we exploit to identify a causal link from ETF liquidity to tracking errors.

[22] For the exact condition to be a threshold stock, see Section 2.4.

[23] An exception for market makers is allowed for either a long sale or bona fide market-making activities. As a result of the amended Reg SHO Rule 204, the size of FTDs steadily increased to more than $7 billion ($2.5 billion for ETFs) at the end of 2007. Despite the gradual decline in FTDs after 2008, ETFs still account for a significant amount of FTDs. About 80% of total FTDs occurred in ETFs at the end of 2016. See Fig. 2 and Table 2 of Evans et al. (2017).

We examine ETFs that are classified as threshold securities by using the threshold flag as an instrument for ETF liquidity shock. Observing exogenous changes in liquidity over a long period of time is difficult when a stock receives a threshold flag for consecutive days. Therefore, we use the first-day registration of the threshold list as the instrumental variable when a stock receives a threshold flag for consecutive days.

The first-stage estimation regresses daily liquidity measures (relative spread) on a dummy variable indicating a threshold flag along with other control variables used in the second-stage regression.[24] The estimation result of the first stage regression is

$$\text{ETF } \widehat{\text{illiquidity}}_t = -0.0001191 \times \mathit{Threshold}_t + \text{Other controls} \tag{2}$$
$$\text{t-statistics}: \quad [-4.50^{***}]$$

where *Threshold* is a dummy variable indicating a Reg SHO threshold flag for a given ETF. The first-stage regression includes day fixed effects, and standard errors are double-clustered at the fund and day level. The estimated coefficient on *Threshold* is negative and significant, implying that the ETF listed as a threshold security experiences improved liquidity owing to bona fide market-making activities, which is consistent with Evans et al. (2017). The first-stage regression result confirms that the instrument used in the analysis satisfies the relevance condition that the instrumental variable is correlated with the endogenous variable, namely, the ETF liquidity measure.

The second-stage estimation regresses the dependent variable of tracking errors on the fitted liquidity estimated from the first-stage regression along with other control variables. Table 5 reports the results from the ordinary least squares (OLS) panel regressions for comparison without instruments (Columns 1, 2, and 3) and the second-stage estimation (Columns 4, 5, and 6). The daily illiquidity measure is still positively associated with the tracking errors of the ETF-index and ETF-NAV returns at the 1% level of statistical significance. The ETF illiquidity is not associated with the fitted tracking errors of the NAV-index returns. These results are not subject to the concern of daily illiquidity measure being endogenous, and they are consistent with the results from daily and yearly panel regressions. The estimates of the second-stage regressions are larger than are those of the OLS estimates. These results could occur because the relations between ETF liquidity and tracking error are not linear. The two-stage least squares regressions focus on threshold securities, which accompany large sudden liquidity shocks, whereas the OLS regression estimates the average effects of ETF illiquidity on tracking errors in both normal and volatile market conditions.

3.6. Fund characteristics, underlying asset liquidity, and tracking errors

This section examines the extent to which ETF illiquidity affects tracking errors, depending on the creation or redemption method or replication strategy. Bloomberg categorizes ETFs into in-kind, cash, and cash and in-kind according to the create or redeem method and into full replication, optimized, and derivatives-used according to the replication strategy. In the case of in-kind creation or redemption, APs must construct and deliver all underlying assets of relevant ETFs for full replication, some underlying assets for optimized replication, and index-based derivatives for derivatives-used replication. To analyze the effect of ETF illiquidity in relation to ETF characteristics, we analyze the interactions between the ETF illiquidity measure and the fund characteristics in the preceding daily regressions.

The creation or redemption method or the replication strategy could change the impact of ETF illiquidity on tracking errors. On the one hand, the effect of illiquidity should be stronger for ETFs with in-kind creation or redemption or full replication, because they have less choice of what and when to trade. On the other hand, to promote ease of trading and accounting process of APs, ETF companies can choose in-kind creation or redemption with full replication in the case of liquid underlying assets but cash-based creation or redemption in the case of illiquid underlying assets. The effect of illiquidity would be stronger for ETFs with cash creation or redemption or with optimized or derivatives-used replications (Antoniewicz and Heinrichs, 2014).[25] In our sample data, 99% of unleveraged ETFs based on US stocks create or redeem shares by the in-kind method. Leveraged ETFs based on non-US stocks tend to create or redeem shares by the cash method. ETF companies try to replicate the index through physical asset delivery when the index consists of highly liquid assets or easily accessible markets, but they are more likely to prefer the optimized or derivatives approach to the full replication approach for illiquid asset classes, such as emerging markets stocks, bonds, or derivatives, which are difficult for APs to manage. We formally test this idea by including interaction terms between ETF illiquidity and fund characteristics, namely, in-kind, full, optimized, and derivatives, in the daily panel regressions. In these regressions, the main dependent variable is the tracking error between the ETF returns and the NAV returns, because we are interested in how ETF illiquidity affects the deviation of the former returns from the latter returns owing to the fund structures or characteristics.

Table 6 reports the effects of ETF illiquidity and the interaction terms between ETF illiquidity and fund characteristics. We include the interaction terms and all the control variables used in the previous analysis and add day fixed effects. Furthermore, standard errors are double-clustered at the fund and day level. Consistent with previous results,

[24] For a robustness check, we run similar two-stage least squares regressions with other liquidity measures, such as effective spread, quoted spread, and relative quoted spread. The main results do not change qualitatively even with other liquidity measures. Those results are reported in Appendix C.

[25] According to Antoniewicz and Heinrichs (2014), the ETF company can allow or require APs to substitute cash for some or all of the assets in the creation basket when acquiring or delivering assets that constitute the index is difficult.

Table 6
Tracking error regression on fund characteristics.
This table reports coefficients estimates of daily regressions of exchange-traded fund (ETF) tracking errors on ETF illiquidity and interaction terms between ETF illiquidity and fund structure variables. The dependent variables are daily tracking errors between ETF and its net asset value (NAV), calculated by taking the absolute values of daily return differences between ETF and its NAV. Columns 1–4 are pooled ordinary least square estimation results for whole sample, and Column 5 is the result for the subsample with non-leveraged US equity–based ETFs without using derivatives to construct funds. All other daily variables are defined in Appendix B. All regressions include day fixed effects. t-statistics based on standard errors double-clustered at the fund and day level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)
ETF Illiquidity	0.768***	0.686***	0.558***	0.504***	0.636***
	(11.38)	(12.50)	(11.01)	(11.44)	(7.62)
ETF Illiquidity × In-Kind	−0.356***				−0.063
	(−4.66)				(−0.42)
ETF Illiquidity × Full		−0.308***			
		(−4.77)			
ETF Illiquidity × Optimized			−0.112		
			(−1.62)		
ETF Illiquidity × Derivatives				0.484***	
				(4.13)	
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	1,155,597	1,155,597	1,155,597	1,155,597	535,280
Adjusted R^2	0.221	0.221	0.220	0.220	0.231

Table 6 confirms that ETF illiquidity has a positive and significant effect on the ETF-NAV tracking errors. Column 1 shows that the coefficient on the interaction term of in-kind is negative with statistical significance. The extent to which ETF illiquidity affects tracking errors is smaller for in-kind ETFs. These results do not support the hypothesis that the influence of ETF illiquidity on ETF tracking error is expected to increase for in-kind ETFs, because the operational costs of APs can increase owing to the direct delivery of the physical assets in the funds. The selection bias could be due to the creation or redemption method that the ETF company chooses at the time of setting up the fund. In other words, when ETF companies set up their funds, they could prefer the cash method to the in-kind method if APs are difficult to create or they could redeem basket portfolios because the assets included in the index are not liquid enough. As a result, the ETF tracking errors with in-kind creation or redemption presumably are less sensitive to illiquidity than are those with other methods.

We further examine the claim that the in-kind ETFs are less sensitive to liquidity by investigating the extent to which ETF liquidity affects tracking errors according to the fund's replication strategy (full, optimized, or derivatives-based). We expect ETF companies to choose the full replication method that includes all the constituents of an index if APs can easily construct the underlying portfolios but can replicate the index using an optimized method or derivatives if the replication is not easy. The effect of ETF illiquidity on tracking errors is expected to strengthen when the company uses replication methods with derivatives, that are optimized, and that are full replication, in that order. Columns 2-4 analyze the interaction terms between full, optimized, and derivative-based indicator variables and ETF illiquidity, respectively.

Consistent with these arguments, the analysis confirms that ETFs with the full replication method (Column 2) are less affected by the ETF illiquidity on tracking errors. ETFs with the optimized (Column 3) or derivatives (Column 4) method have no effects, or the illiquidity effects become stronger. Thus, ETF illiquidity has a different effect on tracking errors depending on the ETF structures. These results imply that ETF companies endogenously choose the creation or redemption method and replication strategy according to the liquidity of the underlying assets at ETF inception. Column 5 analyzes only ETFs that invest in the US equity-based ETFs without choosing derivatives for their replication strategies. The coefficient on the interaction term between ETF illiquidity and in-kind methods becomes statistically insignificant (Column 5). In summary, the results show that ETFs with full replication are less likely to have tracking errors than are ETFs with optimized or derivatives replication.

Our previous analysis reports evidence that the illiquidity of the ETFs choosing the in-kind methods reduces the effect on tracking errors. This result is consistent with the idea that ETF companies can strategically choose replication methods based on their ability to construct portfolios when ETFs are incepted. Thus, the effect of ETF illiquidity on its tracking error due to the liquidity difference of the underlying assets must be examined. We restrict our sample to physical replication ETFs investing in the same asset classes so that we exclude the endogenous choice of the ETF company's replication strategy. We investigate the effects of the ETF illiquidity on tracking errors when a difference exists in the liquidity of the underlying assets by analyzing only those ETFs that invest in US stocks.

Following Ben-David et al. (2018), we identify US equity-based ETFs from Bloomberg and then obtain the holding information for each ETF from the Thomson 12D database. We calculate the weighted average of the underlying asset illiquidity in each ETF by using the mutual fund holding data and the individual stock liquidity measures computed from the TAQ. To compute the fund's liquidity correctly, we select only ETFs whose total stock values of each fund are greater than 90% of the ETF's total asset value at the reporting date. We assume that the individual stock weights of each portfolio calculated on the reporting date are constant on a daily basis, from the previous

Table 7
Underlying asset liquidity and exchange-traded fund (ETF) liquidity.
This table reports coefficients estimates of daily regressions of ETF tracking errors on ETF illiquidity, underlying portfolio illiquidity, and an interaction term between the two. The dependent variables are daily tracking errors, calculated by taking the absolute values of daily return differences between ETF and its index (Columns 1 and 4), between ETF and its net asset value (NAV) (Columns 2 and 5), or between NAV and its index (Columns 3 and 6). We include only non-leveraged US equity–based ETFs to identify underlying portfolio information correctly from Thomson 12D data. The identified sample is 359 US equity-based ETFs. We use the daily relative effective bid–ask spread computed from the NYSE trade and quote (TAQ) database for illiquidity variables of both ETFs and underlying portfolios. The underlying portfolio illiquidity is the value-weighted average of daily relative effective bid–ask spreads of stocks included in each portfolio. All other daily variables are defined in Appendix B. All regressions include day fixed effects. t-statistics based on standard errors double clustered at the fund and day level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	|ETF-IND|		|ETF-NAV|		|NAV-IND|	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
ETF Illiquidity	0.315***	0.509***	0.320***	0.525***	−0.007	0.027**
	(3.32)	(5.99)	(3.16)	(6.02)	(−0.24)	(2.02)
Under Illiquidity	0.161	0.760**	0.284	0.917***	0.211	0.315
	(0.47)	(2.09)	(0.94)	(2.60)	(0.77)	(1.11)
ETF Illiq × Under Illiq	219.042**		227.269**		38.229	
	(2.37)		(2.31)		(1.38)	
Log(AUM)	−0.001***	−0.001***	−0.001***	−0.001***	0.000**	0.000**
	(−4.50)	(−4.33)	(−4.17)	(−3.98)	(2.11)	(2.18)
Log(Dollar Trading Volume)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.66)	(0.47)	(0.38)	(0.14)	(0.86)	(0.81)
Absolute Order Imbalance	0.000*	0.000*	0.000*	0.000*	−0.000	−0.000
	(1.82)	(1.73)	(1.82)	(1.73)	(−1.14)	(−1.21)
Intraday Volatility	0.000*	0.000*	0.000*	0.000*	0.000	0.000
	(1.78)	(1.78)	(1.82)	(1.82)	(1.29)	(1.28)
Shares Outstanding Growth	0.000**	0.000**	0.000	0.000	−0.000	−0.000
	(2.32)	(2.24)	(0.28)	(0.21)	(−1.62)	(−1.63)
Log(Shares Outstanding)	0.000	0.000	0.000	0.000	−0.000	−0.000
	(1.33)	(1.20)	(1.48)	(1.33)	(−1.37)	(−1.41)
Futures Available	0.000**	0.000***	0.000**	0.000**	0.000	0.000
	(2.52)	(2.62)	(2.31)	(2.42)	(0.64)	(0.66)
Options Available	−0.000*	−0.000**	−0.000	−0.000	−0.000	−0.000
	(−1.92)	(−1.97)	(−1.51)	(−1.54)	(−0.38)	(−0.39)
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	425,735	425,735	449,322	449,322	425,735	425,735
Adjusted R^2	0.326	0.325	0.306	0.304	0.223	0.223

reporting date to the reporting date, because mutual funds report their holding information on a monthly or quarterly basis. Based on this computation, we investigate whether underlying liquidity affects ETF tracking errors and, if so, how the interaction between underlying asset liquidity and ETF liquidity affects the ETF's tracking errors.

Table 7 reports the regression results of illiquidity of the underlying portfolio and interactions with ETF illiquidity on ETF tracking errors. We include both fund and day fixed effects, because we include only non-leveraged US equity-based ETFs in this regression. Standard errors are double clustered at the fund and day level.

The even numbered columns confirm that ETF illiquidity is still positive and significant after controlling for illiquidity of underlying portfolios, which is also positive and significant. These results confirm that not only ETF illiquidity, but also underlying asset illiquidity, is an important factor in determining ETF tracking errors. The coefficient on the underlying asset illiquidity becomes insignificant while the coefficient on the ETF illiquidity is still positive and significant when we include the interaction term of the underlying assets and ETF illiquidity. The interaction terms of the two variables are positive and significant, implying that ETF illiquidity is more impactful when underlying assets are less liquid.

In summary, ETF liquidity, not underlying assets liquidity, is a critical factor in determining tracking errors. More important, ETFs investing in less liquid assets produce greater tracking error even if they invest in the same asset classes of the same market. As a result, Table 7 shows that ETF illiquidity is a very crucial variable affecting ETF tracking errors and that the lower the liquidity of underlying assets is, the greater the impact of ETF illiquidity on tracking errors is.

4. The effect of ETF liquidity on returns

Having shown that ETF illiquidity increases tracking errors, we examine the effect of ETF liquidity on expected returns. ETF investors require additional returns for holding less liquid ETFs, because less liquid ETFs have more tracking errors and more transaction costs. To formally test whether ETF liquidity is priced, we adopt the LCAPM developed by Acharya and Pedersen (2005).

4.1. Liquidity-adjusted asset pricing model

The LCAPM leads to three different types of risk premium associated with liquidity risk and market risk. Acharya and Pedersen (2005) argue that asset price

Table 8
Properties of value-weighted portfolios.

This table presents the characteristics of ten value-weighted liquidity and tracking error portfolios. The ten liquidity portfolios are constructed for each month m by ranking all exchange-traded funds (ETFs) with their liquidity measures at the end of month $m-1$. The liquidity (c) for each month is the average of the daily relative effective half-spread of each ETF with at least 15 observations in each month. The ten tracking error portfolios are formed for each month m by sorting the ETFs with at least 15 observations in the previous year with tracking error. The tracking error ($|1-\theta|$) is defined as the absolute difference between one and the estimated coefficient (θ) from the regression of the ETF return on the underlying index return. *Prem* is the ETF premium or discount, defined as the difference between the ETF price and the net asset value (NAV) divided by the NAV. *trn* denotes the daily ETF turnover defined as the trading volume divided by the ETF shares outstanding. $\sigma(r^p)$ is the standard deviation of the daily portfolio return. $\sigma(r^{e,p})$ is the standard deviation of the daily portfolio excess return on the underlying index return. Numbers in parentheses are t-statistics.

	β^{1p} (0.10)	β^{2p} (0.10)	β^{3p} (0.10)	β^{4p} (0.10)	$E(c^p)$ (%)	$\|1-\theta\|$ (%)	*Prem* (%)	*trn* (%)	$\sigma(r^p)$ (%)	$\sigma(r^{e,p})$ (%)
Panel A: Illiquidity portfolios										
1	11.137	0.000	−0.017	−0.012	0.024	9.844	0.042	10.945	1.310	0.292
	(212.77)	(160.92)	(−10.24)	(−11.49)						
2	10.881	0.001	−0.016	−0.016	0.049	13.676	0.089	6.484	1.317	0.382
	(149.55)	(31.55)	(−9.69)	(−5.29)						
3	10.142	0.001	−0.013	−0.020	0.062	15.115	0.072	6.094	1.256	0.434
	(125.26)	(89.35)	(−8.33)	(−10.99)						
4	9.282	0.001	−0.016	−0.026	0.075	14.118	0.103	9.100	1.165	0.525
	(114.80)	(84.54)	(−11.18)	(−9.35)						
5	9.666	0.001	−0.016	−0.031	0.088	13.943	0.061	6.584	1.358	0.678
	(73.04)	(71.06)	(−9.63)	(−9.24)						
6	10.001	0.001	−0.016	−0.035	0.108	14.191	0.052	5.062	1.307	0.470
	(93.86)	(60.72)	(−10.09)	(−8.71)						
7	11.276	0.001	−0.016	−0.044	0.133	17.092	0.037	3.185	1.442	0.506
	(104.17)	(44.44)	(−9.19)	(−8.27)						
8	10.524	0.002	−0.018	−0.060	0.168	21.476	0.037	2.110	1.337	0.607
	(107.12)	(37.35)	(−11.21)	(−7.45)						
9	10.421	0.002	−0.020	−0.091	0.234	22.361	−0.013	1.612	1.317	0.615
	(110.07)	(35.50)	(−12.60)	(−9.00)						
10	10.028	0.003	−0.020	−0.105	0.397	24.932	−0.047	1.381	1.302	0.618
	(96.34)	(26.85)	(−12.85)	(−5.83)						
Panel B: Tracking error portfolios (regression)										
1	10.869	0.001	−0.015	−0.017	0.048	4.996	0.033	8.564	1.343	0.228
	(124.28)	(65.59)	(−8.99)	(−8.62)						
2	11.591	0.001	−0.017	−0.015	0.044	4.929	0.024	8.737	1.397	0.373
	(150.46)	(60.38)	(−10.33)	(−6.28)						
3	11.405	0.001	−0.016	−0.020	0.046	5.322	0.026	9.264	1.376	0.197
	(149.02)	(60.22)	(−9.44)	(−9.09)						
4	11.149	0.001	−0.016	−0.012	0.049	5.953	0.026	9.135	1.346	0.241
	(148.13)	(46.96)	(−10.13)	(−5.26)						
5	11.082	0.001	−0.016	−0.025	0.051	7.820	0.041	8.934	1.362	0.317
	(128.40)	(44.45)	(−9.49)	(−11.13)						
6	10.791	0.001	−0.016	−0.022	0.053	9.224	0.043	8.040	1.347	0.347
	(115.96)	(26.92)	(−9.79)	(−6.81)						
7	10.598	0.001	−0.018	−0.025	0.068	12.895	0.104	6.039	1.359	0.557
	(100.70)	(26.70)	(−11.20)	(−7.68)						
8	10.531	0.001	−0.018	−0.012	0.078	17.134	0.165	4.301	1.388	0.809
	(89.65)	(18.27)	(−11.08)	(−2.71)						
9	9.891	0.001	−0.018	−0.025	0.085	25.181	0.210	3.543	1.332	0.942
	(82.57)	(25.02)	(−11.41)	(−6.25)						
10	7.469	0.000	−0.013	−0.023	0.088	40.993	0.212	2.945	1.131	1.007
	(59.60)	(15.88)	(−9.51)	(−5.58)						
Panel C: Tracking error portfolios (excess return volatility)										
1	10.631	0.001	−0.015	−0.012	0.037	3.841	0.022	9.577	1.279	0.118
	(152.53)	(71.06)	(−9.82)	(−6.58)						
2	10.591	0.001	−0.017	−0.017	0.039	4.814	0.023	8.284	1.274	0.144
	(153.66)	(63.31)	(−10.78)	(−9.78)						
3	9.913	0.001	−0.014	−0.014	0.043	6.214	0.045	9.153	1.217	0.143
	(129.63)	(55.77)	(−9.33)	(−7.85)						
4	9.924	0.001	−0.013	−0.023	0.050	8.620	0.066	9.960	1.260	0.173
	(105.62)	(56.40)	(−8.43)	(−9.13)						
5	9.593	0.001	−0.013	−0.021	0.060	12.218	0.092	9.900	1.235	0.265
	(99.70)	(54.53)	(−8.98)	(−8.25)						
6	9.588	0.001	−0.013	−0.025	0.078	13.636	0.088	10.827	1.375	0.374
	(68.42)	(31.17)	(−8.06)	(−5.29)						
7	9.489	0.001	−0.014	−0.031	0.090	15.895	0.121	7.947	1.328	0.627
	(73.14)	(26.26)	(−8.46)	(−6.28)						
8	10.717	0.001	−0.021	−0.020	0.098	20.580	0.170	3.963	1.428	0.905
	(85.94)	(13.28)	(−12.44)	(−3.31)						
9	11.469	0.000	−0.017	−0.035	0.092	26.563	0.207	3.068	1.511	1.103
	(89.48)	(17.69)	(−9.16)	(−8.83)						
10	11.500	0.001	−0.018	−0.032	0.109	38.643	0.170	5.401	1.622	1.435
	(71.34)	(15.60)	(−9.16)	(−5.31)						

reflects these risk premiums. Under the LCAPM, the liquidity-adjusted net asset return has linear relations with the net market return after considering market liquidity. Acharya and Pedersen (2005) show that individual net return can be expressed as

$$E(r_t^i - r_t^f) = E(c_t^i) + (\beta^{1i} + \beta^{2i} - \beta^{3i} - \beta^{4i})E(r_t^M - c_t^M - r^f), \quad (3)$$

where the four betas are defined as

$$\beta^{1i} = \frac{cov(r_t^i, r_t^M)}{var(r_t^M - c_t^M)}, \quad (4)$$

$$\beta^{2i} = \frac{cov(c_t^i, c_t^M)}{var(r_t^M - c_t^M)}, \quad (5)$$

$$\beta^{3i} = \frac{cov(r_t^i, c_t^M)}{var(r_t^M - c_t^M)}, \quad (6)$$

and $\beta^{4i} = \frac{cov(c_t^i, r_t^M)}{var(r_t^M - c_t^M)}$ (7)

From Eq. (3), the net beta consists of four different betas. In addition to the conventional market beta (β^{1i}), three liquidity betas appear, representing the relations between market liquidity and the individual asset liquidity (β^{2i}), between market liquidity and the individual asset return (β^{3i}), and between individual asset liquidity and the market return (β^{4i}).

Moreover, β^{2i}, representing the relations between individual liquidity and market liquidity, is expected to be positive. Illiquid stocks tend to have large values for β^{2i}, implying that they are significantly affected by the lack of liquidity when the market is illiquid. β^{3i}, representing the relations between the individual asset return and market liquidity, is expected to be negative. The expected return on the illiquid stock decreases further, because the illiquid assets should be sold at a lower price than expected when the market is illiquid. β^{4i} also has a negative value. It measures the relations between the market return and the individual stock liquidity. This negative value implies that the expected return on the illiquid asset decreases when the market declines.

Because ETFs are traded in exchanges like general common stocks, ETF market liquidity also affects the expected return of individual ETFs. An ETF whose liquidity is lower than the ETF market liquidity perhaps cannot replicate the underlying index correctly. In other words, the price of the liquid ETF immediately reflects the movement of the underlying index when the underlying index changes. Insufficient trading can cause the illiquid ETF to fail to track the underlying index accurately. As a result, a tracking error can occur if the ETF suffers from a lack of liquidity owing to insufficient trading activity.

The tracking error could be caused by the liquidity of the underlying securities in ETF baskets. The NAV perhaps does not fully reflect the current value of the underlying index owing to the illiquidity of the underlying securities in the case of in-kind ETFs. If the underlying securities of the ETF are not traded actively in the market, APs fail to properly create or redeem the ETF units. Section 3 confirms that the effects of illiquid underlying assets also affect ETF tracking errors. However, the effects of ETF illiquidity are a more important factor for affecting ETF tracking errors. Thus, we focus on ETF illiquidity to investigate the effect of ETF illiquidity on ETF return and variance.

To investigate the ETF liquidity effect, we first estimate the portfolio betas of LCAPM by using ten liquidity and ten tracking error portfolios. Calculating portfolio betas can bring out important information on the individual ETF characteristics being lost, because each ETF has its own benchmark index and tracks that index instead of the entire ETF market. To mitigate these concerns, we compute the betas for each individual ETF and report the value-weighted average of the betas within each portfolio by assuming that the corresponding underlying index return for each ETF is treated as the market return.

4.2. Portfolio construction

We construct ten liquidity portfolios and ten tracking error portfolios to investigate the effect of liquidity on the ETF return. All the ETFs are value weighted within each portfolio.[26] The ten liquidity portfolios are constructed for each month m by ranking all ETFs with their liquidity measures at the end of month $m-1$. The liquidity for each month is the average of the daily relative effective half-spread of each ETF having at least 15 observations in each month. Ten tracking error portfolios are formed for each year y by sorting the ETFs with at least 60 observations in the previous year. We use two tracking error measures to construct tracking error portfolios. The daily portfolio returns are the value-weighted average of ETF daily returns included in each portfolio.

The daily market return is computed as the value-weighted average of the underlying index return for each ETF used in constructing portfolios. The underlying index return tracked by each ETF is not traded in the market. The use of the underlying index return to calculate the market return can avoid potential measurement errors due to the trading effects, that is,

$$r_t^M = \sum_{i=1}^{N_t} w_t^i f_t^i, \quad (8)$$

where w_t^i is each ETF i's NAV weight at time t and f_t^i is the index return of each ETF i at time t. The daily market liquidity is calculated by taking the value-weighted average of the relative effective bid-ask spreads of all ETFs included in the portfolio's construction. The daily portfolio liquidity is the value-weighted average of the relative effective bid-ask spreads of the securities included in each portfolio, that is,

$$c_t^p = \sum_{i \in p} w_t^{i,p} c_t^i, \quad (9)$$

where $w_t^{i,p}$ is each ETF i's NAV weight at time t and c_t^i is ETF i's daily relative effective spread.

[26] We also construct the equal-weighted portfolio to investigate the liquidity and tracking error effects. We confirm that our results are unchanged. See Appendix C for more details.

Given the persistence of liquidity, using liquidity innovation, instead of the observed relative effective bid-ask spread, is desirable to compute the LCAPM betas. The liquidity innovation of each security is obtained from the fitted residual of the following $AR(2)$ specification.

$$c_t^i = a_0 + a_1 c_{t-1}^i + a_2 c_{t-2}^i + u_t^i \tag{10}$$

The portfolio and market liquidity innovations are calculated in the same way.

4.3. Liquidity risk

Table 8 shows the characteristics of the liquidity portfolios (Panel A) and the tracking error portfolios (Panels B and C). The liquidity and tracking error portfolios show similar patterns. The transaction cost and tracking error increase as liquidity decreases or vice versa, even if the portfolios are constructed based on past illiquidity and the past tracking error of the ETF. This result implies that both illiquidity and the tracking error of the ETF are persistent.

Panel A of Table 8 reports that the expected transaction cost ($E[c]$) is shown to increase monotonically from Portfolio 1 through Portfolio 10. For instance, the expected transaction cost for Portfolio 1, which is the most liquid portfolio, is only 0.024%, and that of Portfolio 10 is 0.397%. Although the liquidity cost differences between Portfolios 1 and 10 are reduced for the tracking error portfolios in Panels B and C, the increasing pattern in the liquidity cost through the portfolios is similar to the liquidity portfolios. The turnover rate, which measures how an ETF is actively traded in the market, is shown to be lower in the low liquidity portfolio than in the high liquidity portfolio.

The portfolio volatility in Column 9 shows no large difference across the portfolios. The volatility of the difference between the ETF and the underlying index return, which is another definition of the tracking errors, increases as liquidity decreases. This result implies that illiquid ETFs cannot perfectly follow the underlying index return and that ETF illiquidity and its tracking errors are positively related.

The relations between illiquidity and tracking error are well illustrated from the distribution of the tracking error in Column 6 of Table 8. The tracking error for the low liquidity portfolio appears to be larger than that for the high liquidity portfolio. The ETF returns with low liquidity tend to deviate more frequently from the ETF's underlying index returns. The average premium of the ETF relative to the NAV is positive and increases as liquidity decreases. ETF arbitrageurs try to trade the ETF close to the publicly announced NAV price or the underlying index. If an ETF does not have enough liquidity so that traders cannot immediately trade the ETF to respond to the movement of the underlying index, then the ETF market illiquidity causes a disparity between the ETF price and the underlying index.

For convenience, the estimated betas are reported by a multiplication of ten. Not surprisingly, β^{1p}, measuring the market risk, is close to one, which implies that the ETFs in the US stock exchange appropriately track the underlying index on average. The three liquidity betas also appropriately reflect the characteristics of the liquidity, even though the magnitude is small. β^{2p}s, indicating the relations between market liquidity and individual liquidity, are positive, implying that individual liquidity decreases when market liquidity decreases. Illiquid ETFs have large values for β^{2p} and are more sensitive to market liquidity shocks. As expected, both β^{3p} and β^{4p} have negative values. The illiquid ETFs or high-tracking error portfolios tend to have large absolute values for β^{3p} and β^{4p}. These results suggest that illiquid ETFs are more likely to deviate from their underlying index returns and are more sensitive to the change in the market return or the market liquidity.

This discussion relies on the portfolio betas not the individual ETF betas. Calculating the individual ETF betas is desirable, because each ETF is designed to follow the specific underlying index. Considering the underlying index return as the individual ETF's market return, the calculated betas can provide more reliable measures to understand individual liquidity risk than the portfolio betas do. Based on this argument, we provide the value-weighted average of betas in each portfolio after estimating the individual ETF betas. The yearly portfolios are formed using the same method as the previous portfolio beta calculation. Table 9 reports the value-weighted average betas of the liquidity and tracking errors of individual ETFs. Overall, the results are similar to the patterns in the portfolio betas. The illiquid ETFs tend to be more sensitive to market liquidity or the market return. The illiquid ETFs also are more likely to deviate from their underlying index returns.

In summary, liquidity is an important factor in determining the ETF return and widens the ETF tracking errors with respect to the underlying index or NAV returns. The estimated portfolio betas suggest that liquidity risk is the undiversified systematic risk, even for constructing the portfolio. Liquidity risk is closely related to ETF tracking errors. In general, ETF liquidity plays an important role in eliminating arbitrage opportunities in the ETF market. ETF investments provide a valuable opportunity to invest indirectly in inaccessible markets. If lack of liquidity causes a tracking error, the results of investing in ETFs versus direct investment in that market differ. If the liquidity risk is the systematic risk, which exists even after constructing the portfolio from ETFs, investing in the ETF is less attractive. If there is liquidity risk from investing in the ETF, ETF investors must be compensated for bearing this risk.

4.4. Liquidity premium

This section investigates the effect of liquidity on the expected return of the ETF using a cross-sectional regression with pre-estimated betas. The regression is estimated by the GMM method. Following Acharya and Pedersen (2005), the standard error is calculated by the Newey and West (1987) method with a lag of 2. The following equations are used to estimate the parameters:

$$E(r_t^p) = \alpha + \kappa E(c_t^p) + \lambda \beta^{net,p}, \tag{11}$$

$$E(r_t^p) = \alpha + \kappa E(c_t^p) + \lambda_1 \beta^{1p} + \lambda \beta^{net,p}, \tag{12}$$

and
$$E(r_t^p) = \alpha + \kappa E(c_t^p) + \lambda_1 \beta^{1p} + \lambda_2 \beta^{2p} + \lambda_3 \beta^{3p} + \lambda_4 \beta^{4p}. \tag{13}$$

Table 9
Properties of value-weighted averages of individual exchange-traded funds (ETFs).

This table presents the characteristics of ten value-weighted liquidity and tracking error portfolios based on individual betas of ETFs. The method for constructing portfolios and variable definitions are the same as in Table 8. When estimating individual betas, we use the value-weighted market returns and illiquidity. After estimating yearly betas for each ETF, value-weighted averages within portfolios are reported. Numbers in parentheses are t-statistics.

	β^{1p} (0.10)	β^{2p} (0.10)	β^{3p} (0.10)	β^{4p} (0.10)	$E(c^p)$ (%)	$\|1-\theta\|$ (%)	*Prem* (%)	*trn* (%)	$\sigma(r^p)$ (%)	$\sigma(r^{e,p})$ (%)
Panel A: Illiquidity portfolios										
1	9.288	0.000	−0.013	−0.008	0.022	7.132	0.031	11.963	1.277	0.413
	(108.59)	(2.74)	(−3.40)	(−4.83)						
2	8.824	0.000	−0.013	−0.009	0.043	12.636	0.116	9.746	1.533	0.657
	(62.68)	(2.37)	(−2.69)	(−3.59)						
3	8.902	0.001	−0.013	−0.017	0.052	12.405	0.110	5.303	1.501	0.722
	(37.54)	(2.38)	(−2.58)	(−3.55)						
4	9.160	0.000	−0.010	−0.019	0.066	9.484	0.065	5.919	1.785	0.701
	(40.58)	(1.89)	(−3.37)	(−5.04)						
5	9.284	0.001	−0.012	−0.019	0.078	8.378	0.068	6.560	1.651	0.627
	(63.45)	(2.43)	(−3.10)	(−3.88)						
6	9.316	0.000	−0.009	−0.028	0.091	8.774	0.077	6.085	1.718	0.639
	(47.31)	(1.78)	(−6.61)	(−2.62)						
7	8.895	0.001	−0.021	−0.028	0.108	15.024	0.198	3.607	1.589	0.749
	(43.87)	(0.78)	(−2.07)	(−2.52)						
8	9.074	0.008	−0.135	−0.055	0.133	14.047	0.144	2.249	1.692	0.818
	(39.79)	(1.19)	(−1.16)	(−3.35)						
9	8.569	0.006	−0.034	−0.059	0.165	17.103	0.262	3.194	1.870	1.102
	(62.39)	(0.78)	(−1.58)	(−3.27)						
10	8.909	0.003	−0.016	−0.137	0.258	14.595	0.211	1.515	1.545	1.034
	(38.44)	(2.05)	(−3.28)	(−5.34)						
Panel B: Tracking error portfolios (regression)										
1	9.777	0.000	−0.010	−0.010	0.038	2.710	0.025	8.951	1.424	0.292
	(257.06)	(2.10)	(−3.25)	(−2.89)						
2	9.767	0.000	−0.010	−0.012	0.037	2.500	0.020	19.761	1.376	0.251
	(225.92)	(2.58)	(−3.71)	(−3.92)						
3	9.776	0.000	−0.011	−0.012	0.042	2.712	0.032	10.522	1.336	0.231
	(206.08)	(2.84)	(−3.18)	(−3.73)						
4	9.781	0.000	−0.011	−0.012	0.046	3.573	0.045	7.692	1.439	0.342
	(147.71)	(2.25)	(−3.67)	(−3.10)						
5	9.480	0.000	−0.009	−0.013	0.048	5.632	0.088	9.192	1.436	0.477
	(67.34)	(3.05)	(−2.97)	(−4.40)						
6	9.656	0.000	−0.010	−0.013	0.047	4.725	0.036	16.949	1.795	0.484
	(160.60)	(2.06)	(−3.59)	(−3.20)						
7	9.442	0.001	−0.018	−0.024	0.061	7.244	0.109	4.246	1.578	0.907
	(82.12)	(1.97)	(−2.31)	(−3.62)						
8	8.959	0.001	−0.009	−0.019	0.068	12.215	0.182	1.953	1.349	0.895
	(61.90)	(4.00)	(−2.00)	(−6.45)						
9	8.140	0.001	−0.019	−0.045	0.094	19.874	0.169	2.435	1.503	1.120
	(54.72)	(2.78)	(−2.86)	(−2.53)						
10	5.887	0.001	−0.017	−0.014	0.054	41.121	0.205	2.974	1.402	1.334
	(19.90)	(3.01)	(−3.15)	(−6.03)						
Panel C: Tracking error portfolios (excess return volatility)										
1	9.762	0.000	−0.015	−0.011	0.034	2.373	0.021	8.477	1.195	0.173
	(280.85)	(2.47)	(−3.07)	(−4.12)						
2	9.668	0.000	−0.009	−0.009	0.028	3.259	0.026	11.166	1.186	0.193
	(380.60)	(2.35)	(−3.66)	(−3.37)						
3	9.793	0.001	−0.018	−0.013	0.041	3.140	0.021	7.211	1.373	0.243
	(407.02)	(2.50)	(−2.78)	(−4.44)						
4	9.427	0.001	−0.008	−0.019	0.052	7.120	0.106	8.581	1.489	0.341
	(41.39)	(3.11)	(−2.70)	(−4.00)						
5	9.371	0.000	−0.016	−0.013	0.055	9.201	0.046	12.101	1.583	0.393
	(36.81)	(0.32)	(−1.59)	(−3.42)						
6	9.647	0.001	−0.014	−0.023	0.069	7.415	0.159	28.909	1.659	0.551
	(51.20)	(2.41)	(−3.82)	(−4.03)						
7	8.448	0.000	−0.011	−0.018	0.073	18.479	0.131	7.150	1.675	0.776
	(14.59)	(3.42)	(−2.83)	(−3.39)						
8	8.487	0.000	−0.013	−0.030	0.087	16.574	0.269	3.263	1.534	0.988
	(24.36)	(2.89)	(−3.18)	(−2.81)						
9	8.012	0.000	−0.015	−0.021	0.064	20.234	0.207	3.297	1.639	1.244
	(23.91)	(3.02)	(−3.21)	(−3.06)						
10	6.870	0.000	−0.010	−0.025	0.084	31.929	0.162	5.083	2.052	1.821
	(17.67)	(3.22)	(−2.83)	(−2.99)						

Table 10
Liquidity premium from value-weighted portfolio betas.
This table presents the estimated coefficients from cross-sectional regressions of the liquidity-adjusted capital asset pricing model (LCAPM) for ten value-weighted portfolios using daily data during 2002–2012. The odd- and even-numbered lines report the estimation results when κ is fixed as the average daily turnover rate and is treated as the free parameter, respectively. Numbers in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Constant (0.01)	$E(c^p)$ (0.01)	β^{1p} (0.01)	β^{2p} (0.01)	β^{3p} (0.01)	β^{4p} (0.01)	$\beta^{net,p}$ (0.01)
Panel A: Illiquidity portfolios							
1	0.00	5.26					0.04***
	(0.13)						(6.30)
2	0.00	−148.68***					0.04***
	(−1.24)	(−10.51)					(6.35)
3	−0.05***	5.26	−3.58**				3.65**
	(−8.13)		(−2.31)				(2.37)
4	−0.05***	−40.68***	−2.97*				3.05**
	(−8.28)	(−4.25)	(−1.93)				(1.99)
5	0.00	5.26	0.05	215.33	18.47	2.54	
	(−0.11)		(0.58)	(0.47)	(0.29)	(0.20)	
6	0.00	−146.97***	0.05	197.00	18.49	2.32	
	(−1.20)	(−10.42)	(0.61)	(0.43)	(0.29)	(0.18)	
Panel B: Tracking error portfolios(regression)							
1	−0.01***	6.95					0.03***
	(−2.67)						(5.21)
2	−0.01***	−249.41***					0.03***
	(−3.10)	(−7.55)					(5.12)
3	−0.06***	6.95	−19.24**				19.27**
	(−8.88)		(−2.38)				(2.39)
4	−0.06***	−64.94**	−18.94**				18.97**
	(−8.93)	(−2.25)	(−2.35)				(2.36)
5	−0.01**	6.95	−0.05	304.02	−37.54	−2.19	
	(−2.42)		(−0.53)	(0.18)	(−0.82)	(−0.17)	
6	−0.01***	−252.66***	−0.05	309.65	−37.82	−3.00	
	(−2.85)	(−7.66)	(−0.56)	(0.18)	(−0.83)	(−0.23)	
Panel C: Tracking error portfolios(standard deviation)							
1	0.00	7.81					0.03***
	(−0.09)						(4.19)
2	0.00	−288.55***					0.03***
	(−0.68)	(−8.49)					(4.14)
3	−0.05***	7.81	−13.26				13.30*
	(−7.55)		(−1.64)				(1.65)
4	−0.05***	−7.86	−13.27*				13.32*
	(−7.57)	(−0.31)	(−1.65)				(1.66)
5	0.00	7.81	0.01	−63.26	−5.46	−5.27	
	(−0.99)		(0.12)	(−0.14)	(−0.13)	(−0.46)	
6	0.00	−287.29***	0.01	−81.32	−2.10	−5.74	
	(−1.55)	(−8.53)	(0.19)	(−0.18)	(−0.05)	(−0.50)	

The above models are estimated either when the coefficient on the expected trading cost, κ, is fixed as the average turnover rate or when it is considered to be the free parameter. The equations are estimated by either the pre-estimated portfolio betas or the pre-estimated individual ETF betas. The estimated parameters using portfolio betas are reported in Table 10, and those using individual betas are reported in Table 11. In Table 10, Panel A reports the estimated results for the liquidity portfolios, and Panels B and C report the estimated results for the tracking error portfolios. The odd and even numbered lines of each panel report the estimation results when κ is fixed as the average daily turnover rate and treated as the free parameter, respectively.

The first line of each panel of Tables 10 and 11 is the GMM estimation result of Eq. (11). The risk premium is positively significant at the 1% level and is similar to both the liquidity and tracking error portfolios (0.04%, 0.03%, and 0.03%, respectively) when using the fixed κ. The results are unchanged even when κ is estimated as the free estimator (Lines 2 and 4). The negative coefficient for the expected cost, κ, can be interpreted as resulting from the managerial fees for ETFs. The intercepts are negatively significant owing to fixed costs, including the managerial fees from the ETF.

In Lines 3 and 4 of Tables 10 and 11, the risk premium is estimated to separate the liquidity risk from the market risk using Eq. (12). As in Acharya and Pedersen (2005), a substantial multicollinearity problem exists even when using the ETF data. $\beta^{net,p}$ is shown to be positive and significant in all specifications. The coefficient for β^{1p} is negative and significant, which is not necessarily true, because the market premium cannot be negative and the net beta also contains the value of β^{1p}. For example, the estimated

Table 11
Liquidity premium from individual betas estimated from value-weighted market variables.
This table presents the estimated coefficients from cross-sectional regressions of the liquidity-adjusted capital asset pricing model (LCAPM) for individual securities using daily data during 2002–2012. When estimating individual betas, we use the value-weighted market returns and illiquidity. The odd- and even-numbered lines report the estimation results when κ is fixed as the average daily turnover rate and is treated as the free parameter, respectively. Numbers in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Constant (0.01)	$E(c^i)$ (0.01)	β^{1i} (0.01)	β^{2i} (0.01)	β^{3i} (0.01)	β^{4i} (0.01)	$\beta^{net,i}$ (0.01)
1	−0.01***	5.50					0.02***
	(−13.02)						(14.09)
2	−0.01***	−2.15					0.02***
	(−13.02)	(−1.05)					(14.09)
3	−0.03***	5.50	0.07***				−0.01***
	(−22.09)		(16.44)				(−6.45)
4	−0.03***	14.63***	0.07***				−0.01***
	(−21.83)	(6.42)	(16.24)				(−6.18)
5	−0.01***	5.50	0.02***	−0.05**	0.01***	−0.03	
	(−10.34)		(12.63)	(−2.55)	(4.52)	(−1.34)	
6	−0.01***	−5.28***	0.02***	−0.05***	0.01***	−0.03	
	(−12.05)	(−2.59)	(12.73)	(−2.64)	(4.59)	(−1.41)	

market premium using the liquidity portfolio (Panel A, Line 3) is still positive, that is, $-0.0358\beta^{1p} + 0.0365\beta^{net,p} = 0.0007\beta^{1p} + 0.0365(\beta^{2p} - \beta^{3p} - \beta^{4p})$.[27] This result implies that both market and liquidity risks are positively related to the expected ETF return. Lines 5 and 6 report the estimation results of Eq. (12) when each beta is considered a separate variable. None of the estimated coefficients is significant, suggesting the existence of a severe multicollinearity problem.

Economic significance can be found in the investment performance by calculating the return difference between Portfolios 1 and 10. The effect of β^{2p}, β^{3p}, and β^{4p} on the annualized return difference between liquidity Portfolio 1 and Portfolio 10 is 0.004%, 0.006%, and 0.132%, respectively. Thus, the annualized return due to the liquidity risk is approximately 0.142%. The magnitude of liquidity risk is lower than those estimated by previous studies. For example, Acharya and Pedersen (2005) and Lee (2011) estimate the effect of liquidity risk as 1.1% for the US stock market and 1.53% for the global market. Our estimated result implies that the liquidity risk of US ETFs is relatively lower than that of US or global common stocks. Considering the large trading volume of ETFs, the small liquidity risk could be substantial costs for institutional investors who take account of large trading volumes in the US ETF market.

Consistent with Acharya and Pedersen (2005), the effect of the covariance between the ETF's illiquidity and market returns seems to have the largest impact on the expected returns. Furthermore, this liquidity risk is still an important factor even when investing in the tracking error portfolio. The portfolio with a large tracking error gains more excess return than that with a small tracking error. For instance, the total annualized return difference between the regression (standard deviation) tracking Portfolios 1 and 10 is 0.005% (0.027%), consisting of -0.0002% (0.0001%) for β^{2p}, -0.002% (0.003%) for β^{3p}, and 0.007% (0.023%) for β^{4p}. These results imply that the ETF tracking error is related to the ETF's liquidity risk, which is a non-negligible risk in ETF investment.

In summary, ETF liquidity is an important factor for determining the expected return of the ETF because the ETF is traded like a common stock even if it is designed to replicate the particular index return. Moreover, a liquid ETF tends to track its underlying index better than an illiquid one does.

5. The liquidity effect on volatility

In this section, the effect of liquidity on ETF variance is investigated using the Lo and MacKinlay (1990) econometric model. We seek to determine whether a lack of liquidity causes a difference between the NAV return variance and the ETF return variance.

5.1. Non-trading probability and ETF variance

Lo and MacKinlay (1990) develop an econometric model to explain the effect of infrequent trading. They show that non-trading increases the return variance and causes negative serial correlation. If an individual security trades very frequently with no time delays, then the variance of the observed return must be the same as the variance of the true asset return. The increase in the expected non-trading days can cause a gap between the observed return variance and the true return variance.

Evaluating whether infrequent trading can increase the asset return variance with respect to the true return variance is not easy, because the true asset return cannot be observed in general. The NAV return can be considered the ETF's true return, which is publicly announced in the market. Given the assumption that the NAV return is the true ETF return, we can test whether non-trading increases

[27] The market premium is also positive in Panel B because $-0.1924\beta^{1p} + 0.1927\beta^{net,p} = 0.0003\beta^{1p} + 0.1927(\beta^{2p} - \beta^{3p} - \beta^{4p})$. In Panel C, the market premium is 0.0005. Both market premiums in Panels B and C are significant.

Table 12
Comparison of exchange-traded fund (ETF) and net asset value (NAV) return variance.
This table reports the variance differences among ETF return, NAV return, and underlying index return. The variance is calculated for individual ETF from the inception date to the end of 2012 or the delisted date. σ_r^2, σ_v^2, and σ_f^2 denote the annual variance of ETF returns, NAV returns, and underlying index returns, respectively. The underlying index returns are adjusted for the leverage factor. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Category	N	σ_r^2 (%)	σ_v^2 (%)	σ_f^2 (%)	$\sigma_r^2-\sigma_v^2$ (%)	$\sigma_r^2-\sigma_f^2$ (%)	$\sigma_v^2-\sigma_f^2$ (%)
Panel A: Asset category							
Asset allocation	40	13.27	9.23	8.13	4.04***	5.15***	1.11
Commodity	42	21.02	16.99	17.41	4.03	3.61	−0.43
Currency	20	2.58	2.14	2.14	0.44**	0.44**	0.00
Debt	109	2.53	1.23	1.08	1.29**	1.44**	0.15***
Domestic equity	318	12.21	11.07	10.83	1.14***	1.38***	0.24***
Domestic sector	261	19.61	18.57	17.05	1.05	2.56**	1.51
Global equity	327	17.68	11.43	14.68	6.25***	3.00	−3.25
Global sector	147	15.28	10.91	10.51	4.37***	4.77***	0.40
Real estate	43	20.52	18.82	18.31	1.70	2.21*	0.51
Panel B: Leveraged or inversed							
Non-leveraged	1115	10.43	6.78	7.89	3.65***	2.54*	−1.11
Leveraged	192	41.78	42.81	38.79	−1.02*	2.99**	4.01***

the ETF return variance with respect to the NAV return variance. The NAV return can be easily modeled using a single linear factor model, because each ETF is designed to track its particular index. For the NAV return series, we assume the following linear relations between the NAV return and the underlying index return.

$$v_t = \alpha + \beta f_t + \epsilon_t, \tag{14}$$

where v_t is the NAV return and f_t is the underlying index return on day t. If the ETF replicates the underlying index perfectly, then the beta should be close to one and the alpha should be close to the fund's expense ratio. While Lo and MacKinlay (1990) assume that the factor return is serially uncorrelated, assuming that serial correlation exists in the factor return series, is more realistic. The following autoregressive process is suitable to account for the serial correlation of the factor return series:

$$f_t = \phi_0 + \phi f_{t-1} + \xi_t, \tag{15}$$

where ξ_t is zero mean noise with variance σ^2. The coefficient of the lagged return is the well-known autocorrelation function of the $AR(1)$ process and is equal to the autocorrelation of lag 1.

As introduced in Lo and MacKinlay (1990), the following two random variables are defined to explain the ETF return process with the non-trading effect. First, the indicator variable δ_t is set to one if the ETF does not trade at the particular date t with probability p. Second, the indicator variable $X_t(k)$ is set to one if ETF trades at time t but has not traded in k previous periods. The indicator variable $X_t(k)$ can be expressed as

$$\begin{aligned} X_t(k) &= (1-\delta_t)\delta_{t-1}\delta_{t-2}\cdots\delta_{t-k}, \qquad k>0 \\ &= \begin{cases} 1, & \text{with probability} (1-p)p^k \\ 0, & \text{with probability} 1-(1-p)p^k. \end{cases} \end{aligned} \tag{16}$$

Given the definition of the indicator variable $X_t(k)$, the ETF return can be written as

$$r_t = \sum_{k=0}^{\infty} X_t(k) v_{t-k}. \tag{17}$$

From Eq. (17), the daily ETF return and the daily NAV return should be same if the ETF is traded every day. Thus, Eq. (17) means that the ETF return at time t can be expressed as the sum of the NAV returns from time $t-k$ to time t if the ETF has not been traded during the previous k periods. Given the definition of the ETF return in Eq. (17), the variance of the ETF return can be expressed as

$$\begin{aligned} Var(r_t) &= Var(v_t) + \frac{2p}{1-p}(\alpha+\beta\mu)^2 \\ &\quad + \frac{2\phi p}{1-\phi p}\beta^2 Var(f_t). \end{aligned} \tag{18}$$

Eq. (18) shows that the ETF return variance is composed of the NAV return variance and the terms associated with the non-trading and autocorrelation effects.[28] If the ETF trades every day, which means that the non-trading probability is close to zero, then the ETF return variance should be the same as the NAV return variance. The third term, which is related to the product of the non-trading probability and the serial correlation in the underlying index return, is not shown in Lo and MacKinlay (1990).

The important aspect in Eq. (18) is that the non-trading probability plays a critical role in increasing the ETF return variance. The non-trading effect exists although no serial correlation is evident in the underlying index return. The expected return for the ETF is always the same as the NAV return. The non-trading probability does not cause any difference between the ETF return and the NAV return. An

[28] See Appendix C for details about deriving Eq. (18).

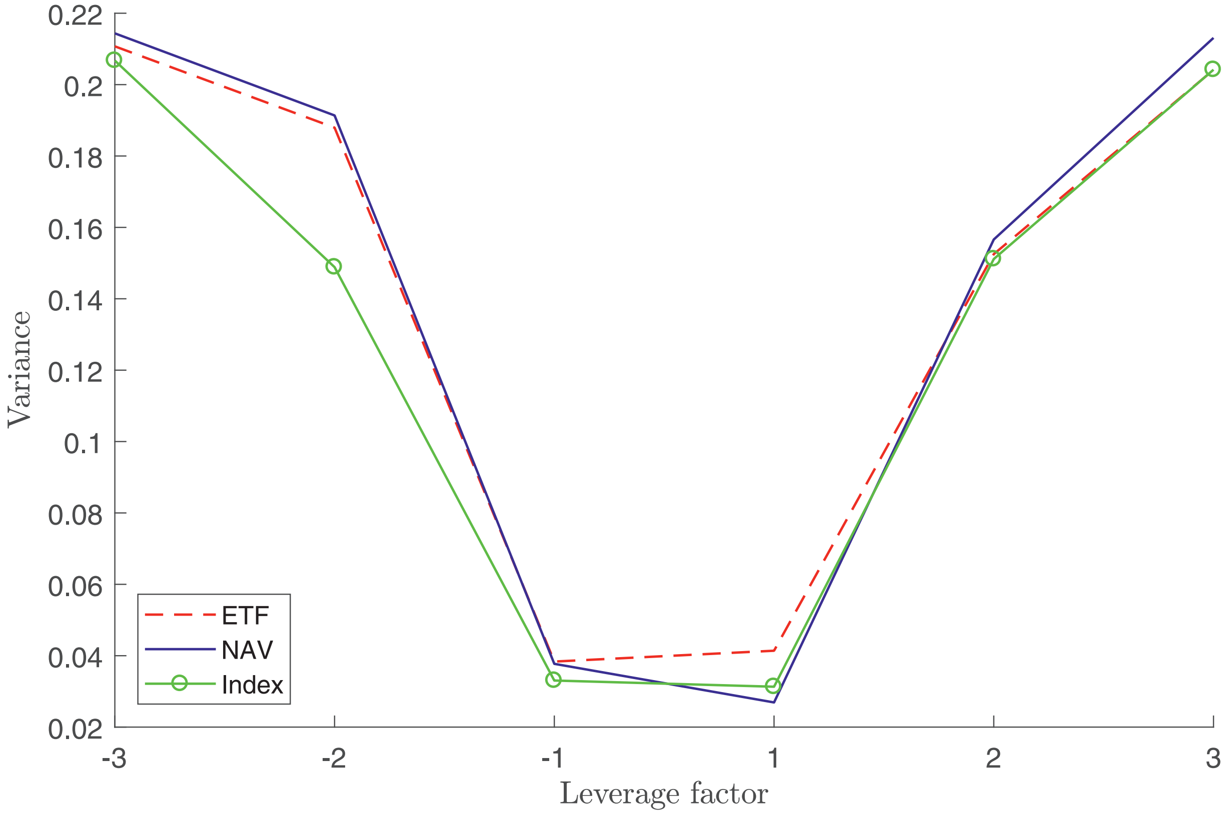

Fig. 9. Variance of exchange-traded (ETF) return, net asset value (NAV) return, and Index return by leverage. This figure illustrates the averages of ETF, NAV, and index return variance by leverage factors. The solid line represents NAV return variance; the dotted line, index return variance; and the dashed line, ETF return variance.

increase in the non-trading probability could cause an increase in the ETF return variance, but not cause any change in the expected return for the ETF. Thus, if an ETF has high probability of non-trading owing to lack of trading volume, the risk of investing in the ETF could increase.

Table 12 reports the variance of each return series and the difference between return variance. The reported variance is the annualized cross-sectional average of each ETF's variance calculated from the daily return series during the sample period. Panel A shows the average of variance by asset category.

Significant differences exist between the ETF return variance and the NAV return variance, except for commodity, domestic or sector, and real estate ETFs. The global or equity-type ETFs tend to have the largest variance difference. Although differences in currency, domestic or equity, and debt ETFs are small, they are still significant. For equity-type ETFs, the variance differences for the ETFs based on US equity are smaller than are those based on international equity.

The difference between the NAV return variance and the index return variance is significant, although it is smaller than that between the ETF return and the NAV return. This result implies that the price movement of the ETF is more volatile than that of the index, suggesting substantial tracking errors in the ETF with respect to the index.

Panel B reports the averages of the variance difference based on whether the ETF is leveraged or unleveraged. On average, leveraged ETFs have higher variance than unleveraged ETFs do. Moreover, the ETF variance is higher than its index return variance regardless of whether the ETFs are leveraged. The variance difference between the ETF and its NAV is bigger in the unleveraged products than in the leveraged products. In addition, no significant difference exists between the NAV return variance and the index return variance for unleveraged ETFs, but a significant difference emerges for leveraged products. This result suggests that leverage can cause an increase in true variance, but it does not necessarily cause an increase in the variance relative to the true variance.

Fig. 9 illustrates the variance of the different return series by the degree of leverage. The variance of the index return is calculated after considering the leverage factor. Fig. 9 shows that the variance also increases when the degree of leverage increases. Furthermore, the plot suggests that the leverage does not necessarily or directly cause an increase in the variance of the trading asset ETFs. In summary, the return variance or volatility increases when the ETF is not actively traded in the market.

Table 13
Non-trading probability and variance difference.
This table presents the summary statistics of variance, non-trading probability, and the expected no trading day of exchange-traded funds (ETFs). In addition, the first-order autocorrelation, the $AR(1)$ coefficient, and the sum of the autocorrelations from lag 1 to lag 10 for the underlying index returns are reported. All statistics are calculated from the daily return series for the entire sample period. σ_r^2 and σ_v^2 denote the variance of ETF returns and the variance of NAV returns, respectively. Non-trading probability, p, is the ratio of non-trading days to total trading days. $E(k)$ is calculated by $p/(1-p)$. ρ_i denotes the lag i autocorrelation. ϕ denotes the coefficient estimate of $AR(1)$ model for daily index returns.

Category	$\sigma_r^2(\%)$	$\sigma_v^2(\%)$	$\sigma_r^2-\sigma_v^2(\%)$	$p(\%)$	$E(k)day$	$\rho_1(\%)$	$\phi(\%)$
1	10.96	10.63	0.33	0.00	0.00	1.76	1.77
2	17.68	18.14	−0.46	0.12	0.00	−1.25	−1.26
3	21.66	22.32	−0.66	0.27	0.00	1.89	1.88
4	14.49	14.65	−0.16	0.74	0.01	0.95	1.00
5	13.81	13.27	0.54	1.95	0.02	1.27	1.28
6	11.26	10.77	0.49	4.52	0.05	−0.36	−0.37
7	11.76	10.36	1.40	9.17	0.10	1.69	1.67
8	14.70	9.40	5.30	20.03	0.25	2.00	2.09
9	15.66	7.82	7.84	40.23	0.70	−0.51	−1.19
10	25.81	5.97	19.84	67.04	2.41	0.28	0.19

The return variance of the illiquid ETF increases because the price of the illiquid ETF cannot immediately reflect the price of the index. It should reflect all past fluctuations of the index, which are not involved in the price owing to non-trading effects. The lack of liquidity could cause an increase in the risk of investing in the ETF, because it increases the return variance and decreases the ETF performance even if the expected return is independent of illiquidity.

5.2. Non-trading probability and variance difference

In Section 5.1, our model shows how non-trading can affect the ETF return variance compared with the NAV return variance. Based on the derived results, this section provides empirical evidence to support the model. The variance of each ETF is calculated based on the daily data from 2002 to 2012. In the case of an ETF created after 2002, the variance is calculated from the inception date. The non-trading probability is simply defined as the proportion of non-trading days to the actual trading days during the sample period.

Table 13 provides average values for the ETF and NAV return variance classified by non-trading probability. Category 1 contains only ETFs traded every day during the sample period. The non-trading probability of Category 1 is zero. The remaining categories are constructed by sorting ETFs that have at least one non-trading day during the sample period classified by the non-trading probability. The reported variances are annualized for convenience. Eq. (18) shows that the variance difference between the ETF returns and the NAV variance is related not only to the non-trading probability, but also to the autocorrelation of the underlying index return. The average autocorrelations of the index returns are also reported.

Table 13 shows that the non-trading probability is related to the difference between the ETF variance and the NAV variance. As the non-trading probability increases, the difference between both variances also increases. For instance, ETFs included in Category 10 are not traded for 67.04% of the trading days, and the annual variance difference for those ETFs is 19.84%. The number of expected non-trading days also increases when the non-trading probability increases. The ETFs included in Category 10, which show the least trading activity, have not been traded for three consecutive days on average. The autocorrelation with lag 1 (ρ_1) and the $AR(1)$ coefficient (ϕ) for the underlying index return are reported in the last two columns. No clear relation exists between the autocorrelation of the underlying index return and the non-trading probability.

5.3. Panel regression results of variance differences on illiquidity

Eq. (18) shows that the variance difference appears to be closely related to the non-trading probability and autocorrelation. The non-trading probability plays the role of increasing ETF volatility relative to its NAV volatility. The regression analysis is performed to investigate whether the non-trading probability, the autocorrelation of the index return, and the interaction between the two are related to the difference between the ETF return variance and the NAV return variance. In this regression analysis, we use annual variables to control the seasonal effect and to obtain more observations. In each year, the variables are calculated from the daily data for each ETF with more than 60 observations. The annual non-trading probability is calculated from the proportion of the observed data to the market trading days. The primary dependent variable in this regression analysis is the difference between the ETF return variance and the NAV return variance.

Table 14 reports the panel regression results. As seen in Column 1, the coefficient for non-trading probability is positive and significant. This evidence suggests that the risk of ETFs can increase when the ETF is not traded actively in the market. This coefficient is stable even if other control variables are included in Column 4 (0.100 and 0.101).

Columns 2 and 3 of Table 14 investigate the effect of the autocorrelation of the underlying index return

Table 14
Regression of variance difference on non-trading probability.

This table reports coefficient estimates of regressions of variance differences on non-trading probability. The dependent variable is the annual variance difference between exchange-traded fund (ETF) and net asset value (NAV) returns. Non-trading probability, p, is the ratio of non-trading days to trading days each year. ϕ is the coefficient of the $AR(1)$ for daily index returns each year. All independent variables are yearly averages of daily variables. All independent variables are yearly averages of daily variables. All daily variables are defined in Appendix B. All regressions include year fixed effects. t-statistics based on standard errors double-clustered at the fund and year level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Variable	(1)	(2)	(3)	(4)	(5)
Non-trading Prob(p)	0.100***			0.101***	
	(10.21)			(10.39)	
$AR(1)$ Coefficient(ϕ)		0.016***	0.015***	0.023***	
		(3.04)	(2.82)	(5.32)	
$p^*\phi$			0.023	0.009	
			(0.34)	(0.15)	
$p/(1-p)$					0.023***
					(6.76)
$p\phi/(1-p\phi)$					0.062
					(1.19)
Log(AUM)	−0.002	−0.004**	−0.004**	−0.002	−0.003
	(−1.09)	(−2.35)	(−2.35)	(−1.26)	(−1.61)
Log(Dollar Trading Volume)	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(−5.47)	(−4.33)	(−4.37)	(−5.20)	(−5.35)
Log(Shares Outstanding)	0.005***	0.003	0.003	0.005***	0.004**
	(2.96)	(1.47)	(1.47)	(3.03)	(2.39)
Shares Volatility	−0.015	−0.043***	−0.043***	−0.017	−0.022
	(−0.94)	(−2.59)	(−2.59)	(−1.07)	(−1.38)
Equity-Type ETF	0.004*	0.005**	0.005**	0.005**	0.004*
	(1.76)	(2.03)	(2.02)	(2.39)	(1.78)
Invested in US Assets	−0.013***	−0.011***	−0.011***	−0.011***	−0.012***
	(−10.33)	(−7.11)	(−7.10)	(−8.09)	(−9.64)
Swap-Based	0.008	0.004	0.004	0.007	0.007
	(0.94)	(0.41)	(0.43)	(0.80)	(0.76)
Derivatives-Based	−0.000	0.000	−0.000	0.001	−0.001
	(−0.02)	(0.02)	(−0.01)	(0.21)	(−0.10)
Leveraged Fund	−0.013*	−0.020**	−0.020**	−0.012	−0.016*
	(−1.70)	(−2.30)	(−2.29)	(−1.60)	(−1.93)
Futures Available	0.005***	0.014***	0.014***	0.005***	0.009***
	(3.52)	(7.44)	(7.43)	(3.63)	(5.80)
Options Available	0.001	−0.001	−0.001	0.001	0.000
	(1.09)	(−0.64)	(−0.69)	(1.21)	(0.10)
In-Kind	−0.005***	−0.009***	−0.009***	−0.005***	−0.007***
	(−3.10)	(−4.29)	(−4.29)	(−2.73)	(−3.82)
Optimized	−0.001	−0.003***	−0.003***	−0.002	−0.002*
	(−1.23)	(−2.75)	(−2.75)	(−1.43)	(−1.70)
Expense Ratio	−0.005	−0.008	−0.007	−0.006	−0.005
	(−1.35)	(−1.30)	(−1.27)	(−1.36)	(−1.11)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	5,963	5,963	5,963	5,963	5,963
Adjusted R^2	0.215	0.118	0.118	0.219	0.201

on ETF variance. Both estimated coefficients in Columns 2 and 3 are stable (0.016 and 0.015). The existence of autocorrelation in the underlying index return is positively related to the variance difference between ETF returns and the NAV returns. Column 4 considers all three variables: non-trading probability, autocorrelation, and the interaction term between the non-trading probability of the ETFs and the index autocorrelation. Consistent with the previous results, the non-trading probability and the autocorrelation are positively related to the variance difference between the ETF returns and the NAV returns. Column 5 reports the regression result when the related variables are transformed to follow the form in Eq. (18). After including the transformed variables in the regression, the non-trading probability is still positive and significant, but the interaction term is not significant.

In summary, these empirical findings support the relations shown in Eq. (18). ETF variance can increase relative to its NAV variance when the ETF is not actively traded in the market. These results suggest that lack of liquidity due to infrequent trading can increase the risk of ETF investment.

6. Conclusion

The ETF market has grown tremendously over the last two decades. ETFs are now considered more transparent, less expensive, and more tax-efficient than traditional mutual funds. Moreover, ETFs provide an investment opportunity to access other inaccessible markets or asset categories. ETFs in the US markets are one of the popular financial products that have emerged in recent years and, thus, have driven a passive investment era. Despite the large amount of money flowing into ETFs every day, less popular ETFs still are not traded properly.

This study investigates the effect of liquidity on ETF returns and tracking errors. Our empirical analysis shows that illiquid ETFs tend to have large tracking errors. We use the threshold list of ETFs as an instrumental variable to investigate the causal link between the ETF illiquidity and tracking errors. The results confirm that the instrumental variable approach shows a causal link from illiquidity to tracking errors. We also find that both underlying asset illiquidity and ETF illiquidity affect ETF tracking errors. More important, we find that tracking errors of ETFs holding illiquid underlying assets tend to be more sensitive to ETF illiquidity.

We show that liquidity is an important risk factor affecting the ETF returns, which is similar to the case of general common stocks. Our empirical results support the LCAPM in that liquidity risks are priced in the US ETF market. An ETF's required return depends on the covariances of its own liquidity and return with the market liquidity and return. Liquidity risk explains approximately 0.14% of the annual ETF returns. Although the magnitude is smaller than those of US or global common stocks, liquidity risk could be substantial for large institutional traders.

Our second set of empirical tests show that the lack of liquidity increases the ETF variance with respect to the NAV variance. Extending the Lo and MacKinlay (1990) econometric model to consider the autocorrelation of the underlying index return, the ETF variance can be decomposed into the NAV variance and the terms related to the non-trading probability. Our finding implies that the variance of the ETF can increase when the ETF is traded infrequently. The calculated ETF variance is shown to be larger than the NAV variance. The regression analysis shows that the ETF variance is positively related to the non-trading probability.

ETFs are designed to track an index representing specific markets or sectors. Therefore, ETFs should provide the same expected return as the return of the particular index. If ETFs have liquidity risks and, thereby, tracking errors, investors may incur another risk in addition to market risk. ETFs that should replicate the index precisely have different outcomes from index returns owing to secondary market liquidity problems suggested in this study. Our results suggest that ETF liquidity is an important aspect to consider when investors make investment decisions on ETFs.

Appendix A. Sample Construction

Table A1
Study sample.
This table presents the process of constructing the sample used in this study. Initial exchange-traded fund (ETF) data are extracted from the Bloomberg database for all the ETFs that have ever been listed and traded in the US from 1993 through 2012.

Description	Number of ETFs
Initial sample (1)	1,495
ETFs on the BATs global market (2)	17
Actively managed funds (3)	57
Underlying index data are missing	
Barclays Capital Bond Index (4)	68
Combination of commodity prices (5)	11
Index level data are not available (6)	20
NAV data are missing (7)	6
Price data are missing (8)	9
Total number of samples deleted (9) [(2) – (8))]	188
Final sample (1) – (9)	1,307

Appendix B. Variable definition and description

Table B1
Variable definitions.

Variable	Definition	Freq.	Source
Absolute Order Imbalance	Absolute value of normalized order imbalance. Normalized order imbalance is the order imbalance divided by the fund creation and redemption size. Order imbalance is calculated by the difference of the number of trading volume between traded at ask side and traded at bid side.	Daily	NYSE TAQ, Bloomberg
AR(1) Coefficient(ϕ)	Coefficient estimate of the AR(1) model for daily underlying index returns.	Yearly	Bloomberg
AUM	Assets under management, which are net asset value times the number of shares outstanding.	Daily	Bloomberg
Derivatives-Based	Indicator variable of one if the ETF uses the derivatives contracts to replicate its underlying index.	Daily	Bloomberg
Dollar Trading Volume	Trading volume times the daily closing price. Set to zero if no trading volume.	Daily	Bloomberg
Effective Spread	Average of the trade-weighted effective half-spread, which is the absolute difference between the trade price and the quote midpoint of the associated price.	Daily	NYSE TAQ
Equity-Type ETF	Indicator variable of one if the underlying portfolio of the ETF consists of equity.	Daily	Bloomberg
Expense Ratio	Annual expense ratio.	Yearly	CRSP MF, Bloomberg

(continued on next page)

Table B1 (*continued*)

Variable	Definition	Freq.	Source
Futures Available	Indicator variable of one if the ETF has futures contracts based on itself. The futures contracts are available after the approval date of the Commodities Futures Trading Commission (CFTC).	Daily	Bloomberg,CFTC
Index Volatility	Annual standard deviation of daily index returns.	Yearly	Bloomberg,ETF webpage
In-Kind	Indicator variable of one if the ETF delivers or receives physical assets when creating or redeeming shares.	Daily	Bloomberg
Intraday Volatility	Daily standard deviation of intraday price changes.	Daily	NYSE TAQ
Invested in US Assets	Indicator variable of one if the underlying portfolio of the ETF consists of US assets.	Daily	Bloomberg
Leveraged Fund	Indicator variable of one if the ETF is either inverse or leveraged.	Daily	Bloomberg
Non-trading Prob(p)	Number of non-trading days divided by total business days each year.	Yearly	Bloomberg
Optimized	Indicator variable of one if the ETF optimizes the portfolio when replicating its underlying index.	Daily	Bloomberg
Options Available	Indicator variable of one if the ETF has option contracts based on itself. Option contracts are available after the first day recorded in OptionMetrics.	Daily	Bloomberg, Option-Metrics
Quoted Spread	Average trade-weighted half-spread, which is the difference between the ask and bid prices of the quote divided by two.	Daily	NYSE TAQ
ETF Illiquidity	Average relative effective half-spread of the day. The variable is defined as the effective half-spread divided by the trade price in which the effective half-spread is the absolute difference between the trade price and the quote midpoint of the associated price.	Daily	NYSE TAQ
Relative Quoted Spread	Average trade-weighted relative half-spread, which is the half-spread divided by the quote midpoint.	Daily	NYSE TAQ
Shares Outstanding Growth	Log of shares outstanding to the lagged shares outstanding at daily level.	Daily	Bloomberg,ETF webpage
Shares Volatility	Volatility of shares outstanding growth defined as the standard deviation of daily share outstanding growth.	Yearly	Bloomberg,ETF webpage
Shares Outstanding	Number of shares outstanding	Daily	Bloomberg, ETF webpage
Swap Based	Indicator variable of one if the ETF uses the swap contracts to replicate its underlying index.	Daily	Bloomberg
Underlying Asset Liquidity	Weighted average of relative effective spreads of stocks contained in the ETF. Individual weight is computed by dividing the value of each stock by the sum of stock values.	Daily	Thompson 12D, NYSE TAQ

Appendix C. Proof of ETF variance

Under the $AR(1)$ process, the autocovariance of f_t is

$$Cov(f_t, f_{t-k}) = \phi^k Var(f_t). \tag{C.1}$$

For $l > k$,

$$\begin{aligned} E[v_{t-k}v_{t-l}] &= E[(\alpha + \beta f_{t-k} + \xi_{t-k})(\alpha + \beta f_{t-l} + \xi_{t-l})] \\ &= \alpha^2 + 2\alpha\beta E[f_t] + \beta^2 E[f_{t-k} f_{t-l}] \\ &= \alpha^2 + 2\alpha\beta E[f_t] + \beta^2 (E[f_t]^2 + \phi^{l-k} Var(f_t)) \\ &= (\alpha + \beta E[f_t])^2 + \beta^2 \phi^{l-k} Var(f_t) \\ &= E[v_t]^2 + \beta^2 \phi^{l-k} Var(f_t). \end{aligned} \tag{C.2}$$

The second moment of the r_t is

$$\begin{aligned} E[r_t^2] &= E\left[\sum_{k=0}^{\infty} X_t(k) v_{t-k} \sum_{l=0}^{\infty} X_t(l) v_{t-l}\right] \\ &= \sum_{k=0}^{\infty} E\left[X_t^2(k) v_{t-k}^2\right] + 2\sum_{k=0}^{\infty}\sum_{l=k+1}^{\infty} E[X_t(k)X_t(l)]E[v_{t-k}v_{t-l}] \\ &= \left(Var(v_t) + E[v_t]^2\right)\sum_{k=0}^{\infty}(1-p)p^k \\ &\quad + 2\sum_{k=0}^{\infty}\sum_{l=k+1}^{\infty}(1-p)p^l\left(E[v_t]^2 + \phi^{l-k}\beta^2 Var(f_t)\right) \\ &= Var(v_t) + E[v_t]^2 + 2E[v_t]^2 \sum_{k=0}^{\infty} p^{k+1} \\ &\quad + 2\beta^2 Var(f_t)(1-p)\frac{\phi}{1-\phi p}\sum_{k=0}^{\infty} p^{k+1} \\ &= Var(v_t) + E[v_t]^2 + \frac{2p}{1-p}E[v_t]^2 + \frac{2\phi p}{1-\phi p}\beta^2 Var(f_t). \end{aligned} \tag{C.3}$$

The expected return of the ETF return is simply

$$\begin{aligned} E[r_t] &= E\left[\sum_{k=0}^{\infty} X_t(k) v_{t-k}\right] \\ &= \sum_{k=0}^{\infty} E[X_t(k)]E[v_{t-k}] \\ &= E[v_t]\sum_{k=0}^{\infty}(1-p)p^k = E[v_t]. \end{aligned} \tag{C.4}$$

So, the variance of the ETF return is

$$\begin{aligned} Var(r_t) &= E[r_t^2] - E[r_t]^2 \\ &= Var(v_t) + \frac{2p}{1-p}E[v_t]^2 + \frac{2\phi p}{1-\phi p}\beta^2 Var(f_t). \end{aligned} \tag{C.5}$$

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