Do ETFs Increase the Commonality in Liquidity of Underlying Stocks?

VIKAS AGARWAL, PAUL HANOUNA, RABIH MOUSSAWI, and CHRISTOF W. STAHEL*

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ABSTRACT

We examine the impact of ETF ownership on the commonality in liquidity of underlying stocks, while controlling for other institutional ownership. Analyses using aggregate stock-level ETF ownership and common ETF ownership at the stock-pair level indicate that ETF ownership significantly increases commonality. We show that greater arbitrage activities are associated with a larger effect of ETF ownership on commonality. We use quasi-natural experiments that exploit the reconstitution of Russell indexes, and ETF trading halts, to establish the causal effect of ETF ownership and the arbitrage mechanism, respectively. Our results suggest that ETFs reduce investors' ability to diversify liquidity risk.

JEL classification: G10, G12, G14, G23

Keywords: Exchange-Traded Funds (ETFs), Liquidity, Commonality, Arbitrage, Trading Halts, Index Reconstitution

*Vikas Agarwal is from the J. Mack Robinson College of Business, Georgia State University. Paul Hanouna and Rabih Moussawi are both from the Villanova School of Business, Villanova University. Christof W. Stahel is from the Investment Company Institute. We wish to thank Itzhak Ben-David, Serge Darolles, Caitlin Dannhauser, Richard Evans, David Gempesaw, Sebastien Pouget, N.R. Prabhala, Pedro Matos, Avanidhar Subrahmanyam, Kumar Venkataraman, and seminar and conference participants at the University of Buffalo, UC Irvine, University of Cologne, Penn State, the Banque de France, the 2016 India Finance Conference, the 2017 INQUIRE Finance in the 21st Century Conference, the 2017 Ohio State University Alumni Conference, Deutsche Bank's 4th Annual Global Quantitative Strategy Conference, the CQA Trading Seminar, the 2017 Northern Finance Association Annual Meetings, the University of Virginia (Darden), the 28th Annual Conference on Financial Economics and Accounting, and the 5th Annual Conference on Financial Markets Regulation 2018, for helpful discussions and comments. Agarwal, Hanouna and Moussawi acknowledge the generous support of the Lyxor-Paris Dauphine ETF Research Academy. Agarwal would also like to thank the Centre for Financial Research (CFR) in Cologne for their continued support.

The growth in exchange-traded funds (ETFs) over the last several decades has been nothing short of remarkable.[1] Contributing to the rapid success of ETFs are the numerous advantages they provide investors among which are increased access to asset classes and markets, as well as, improved tax efficiency, liquidity, price discovery, and transparency (Hill, Nadig, and Hougan, 2015). However, several recent academic studies have highlighted certain unintended consequences these innovations have on the underlying securities they hold. So far this research has found that ETFs reduce the liquidity (Hamm, 2010), increase the non-fundamental volatility (Ben-David, Franzoni, and Moussawi, 2018), reduce the informational efficiency (Israeli, Lee, and Sridharan, 2017), and increase the co-movement in returns (Da and Shive, 2017) of the underlying securities ETFs invest in. In this paper, we examine how ETFs affect the commonality in liquidity among their component securities. Commonality in liquidity has been shown to have important asset pricing implications. Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) find that liquidity co-moves across securities. The co-movement in liquidity reduces the possibility to diversify individual asset's liquidity risk, giving rise to a liquidity risk factor. This factor has been shown to be priced as investors demand a risk premium for holding assets that are exposed to liquidity risk (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005).

In addition to understanding how ETFs affect the securities they hold, our research sheds light on the sources of commonality in liquidity. Prior research identifies both supply- and demand-based explanations for the factors driving the commonality in liquidity. Supply-based explanations center around the notion that financial intermediaries face systematic capital shocks and funding constraints that prevent them from providing liquidity, especially during market downturns. This, in turn, gives rise to commonality in liquidity, which can lead to systematic liquidity dry-ups (Coughenour and Saad, 2004; Brunnermeier and Pedersen, 2009; Hameed, Kang, and Viswanathan, 2010). In contrast, demand-based explanations focus on correlated trading by individual and institutional investors across assets in response to common sentiments, preferences, or trading signals (Huberman and Halka, 2001; Kamara, Lou, and Sadka, 2008; Koch, Ruenzi, and Starks, 2016). In this paper we contribute to the literature that provides a demand-side explanation for the commonality in liquidity. To the extent that ETFs are themselves traded in the secondary market as the securities they hold, makes our setting distinct from other types of institutions that do not trade in the secondary market.

We conjecture that common ETF ownership of underlying securities give rise to demand-side co-movement of liquidity through the inherent arbitrage mechanism that is designed to ensure that the difference between

[1] Figure 1 shows that assets under management in ETFs have grown to over $2 trillion in 2016, or roughly 9% of the total market capitalization of the US equity market. More impressively, Figure 2 shows that ETF trading volume represents between 25% to 45% of all US equity trading volume and ETF short interest represents between 20% to 30% of all US equity short interest.

the prices of the ETF share and the component securities basket remains narrow. Authorized Participants (APs), and other market participants, attempt to arbitrage away the deviations between the ETF price and the value of the constituting basket. When the ETF is trading at a premium during the trading day, APs sell the ETF short while simultaneously buying the basket. At the end of the trading day, the APs cover their short sales by delivering the basket to the ETF in exchange for ETF shares. Alternatively, when the ETF is trading at a discount, APs buy the ETF shares and short sell the basket. APs unwind their positions at the end of the day by redeeming the ETF shares for the basket. Additionally, other market participants, such as high frequency traders, can also take advantage of the arbitrage opportunities by taking long (short) positions in the ETF and short (long) positions in the constituents of these ETFs (for more institutional details see Ben-David, Franzoni, and Moussawi (2017)). As a result, trading activity in the underlying securities is linked through common ETF ownership, leading to simultaneous trading in these securities. This in turn, is associated with correlated demand for the liquidity of these securities, and therefore, greater commonality in liquidity between them.

In this paper we address the following research questions: First, how does ETF ownership affect the commonality in liquidity of the stocks included in the ETF basket? Second, is the impact of liquidity commonality from ETFs distinct from that of other market participants such as passive and active open-end mutual funds, and other institutional investors, especially in light of the fact that ETFs do not trade the underlying assets? Third, is there a causal relation between ETF ownership and commonality in stock liquidity? Finally, can the arbitrage mechanism explain the effect of ETF ownership on the commonality in stock liquidity?

We measure how the liquidity of a stock co-moves with the liquidity of stocks that have high ETF ownership using a methodology similar to the one laid out in Coughenour and Saad (2004) and Koch et al. (2016). Coughenour and Saad (2004) examine how the liquidity of a stock co-moves with the liquidity of other stocks handled by the same specialist firm. Koch et al. (2016) show that the liquidity of stocks with high mutual fund ownership co-move with that of other stocks that also have high mutual fund ownership. Following the approach in these two papers, we construct a measure of commonality in liquidity and then correlate this measure with the ETF ownership in the stock.

Our analysis reveals several interesting findings. First, stocks having higher ETF ownership exhibit greater commonality in liquidity. Moreover, the relation between ETF ownership and liquidity commonality is not confined to certain stock market capitalization sizes, or to specific market conditions. Furthermore, using a falsification test that randomly assigns ETF ownership to stocks does not yield a significant relation between ETF ownership and commonality in liquidity. Second, the relation between ETF ownership and commonality in liquidity does not seem to be an indexing phenomenon since the ownership by index funds, and the weights of stocks in the major indexes are explicitly controlled for in the analysis. Similarly, the commonality in liquidity that arises from ETF ownership is distinct from that arising from the ownership of active institutional investors.

Additionally, we follow a methodology similar to Antón and Polk (2014) to conduct analysis at the stock-pair level by relating the correlation in changes in liquidity between a stock pair to the common ownership of ETFs in that stock pair. We use two proxies of common ownership, the percentage ownership, and the number of ETFs that hold the stock pair. This alternative approach offers the advantage of not specifying a model to estimate the commonality in liquidity measure. However, one of the limitations of this approach is that it ignores the effect of correlated liquidity shocks of various ETFs that own different stocks, which can lead to co-movement in liquidity without the presence of common ownership (Greenwood and Thesmar, 2011). Our findings from this complementary analysis continues to support our hypothesis that ETF ownership positively affects the commonality in stock liquidity.

We next establish a causal relation between ETF ownership and commonality in liquidity. ETFs are likely to hold stocks that share common characteristics (e.g., market capitalization), which in turn may drive commonality in liquidity rather than ETF ownership. Therefore, to address such potential endogeneity in ETF ownership, we exploit a quasi-natural experiment, using the reconstitution of Russell 1000 and Russell 2000 indexes to capture plausibly exogenous variation in the common ETF ownership (due to the index reconstitution forcing changes in ETF ownership). This helps us establish a causal relation between ETF ownership and co-movement in stock liquidity as opposed to ETFs selecting to invest in stocks that exhibit a higher liquidity co-movement. The reconstitution of Russell indexes can result in changes in the aggregate ETF ownership along with the changes in the common ETF ownership. Therefore, we also employ an instrumental variable approach, similar to Appel, Gormley, and Keim (2016) and Ben-David et al. (2018), to differentiate between changes in aggregate ETF ownership in stocks and the common ownership of ETFs holding the same stock pair. This helps provide a cleaner identification of the causal relation using the switch between indexes as an exogenous instrument for ETF ownership change.

Next, we examine the arbitrage mechanism in ETFs through which ETF ownership contributes to an increase in the commonality in liquidity of their underlying securities. We show that greater ETF arbitrage opportunities and related trading activities are associated with larger increase in commonality in liquidity. This evidence separates our mechanism from those in earlier papers that provide a demand-side explanation to commonality in liquidity. For example, Koch et al. (2016) attribute commonality in liquidity to correlated trading activities by active mutual funds in response to investor inflows and outflows. In contrast, flow-driven liquidity demand is not necessary in the case of ETFs where even in the absence of flows, the arbitrage mechanism can generate commonality in liquidity. This can occur due to the deviation between the prices and NAVs of ETFs on account of any changes in the prices of individual securities constituting the basket. Unlike mutual funds, ETFs are subject to continuous liquidity shocks as high-frequency investors are attracted to ETF liquidity during the day for their various hedging and risk management needs (Huang, OHara, and Zhong, 2018; Ben-David et al., 2018). These shocks can create deviations between the ETF price and its NAV, and consequently trigger arbitrage trading activities. The critical distinction between the economic mechanisms in Koch et al. (2016) and our study is due to the fact that ETFs trade continuously throughout the day unlike open-end funds that can be traded only at the end-of-the-day NAV. Moreover, unlike ETFs, it is not feasible to short open-end funds.

Another distinction between ETFs and open-end funds with commonality in liquidity implications is that ETFs have much less discretion in their trading response to investor flows. ETFs must unequivocally translate investor flows into either creating or redeeming ETF shares by trading in the underlying securities in the exact same proportions as in the ETF creation or redemption units, regardless of the availability, liquidity, or price impact associated with trading the underlying securities. In contrast, managers of open-end funds, have significant discretion on how to respond to investor inflows or outflows, considering their liquidity management requirements and availability of investment opportunities. Therefore, not all investor flows will necessarily translate into trading in the securities held by these funds. In principle, ETFs are perhaps more comparable to passive open-end funds (i.e., index funds). However, again there exist several salient differences. Even though index funds are less discretionary in their trading behavior, their portfolio managers can also exercise some discretion in rebalancing their portfolios in response to changes in the benchmark index. Index funds have the incentives to use this discretion to mitigate losses from front-running by other market participants (Green and Jame, 2011). In contrast, such incentives do not exist for APs that are not centralized, that is they do not exclusively work for a given ETF.

To help identify the arbitrage mechanism driving the relation between ETF ownership and the commonality in liquidity, we use the events of August 24, 2015 when trading was halted in certain ETFs but not in their component securities. Using a difference-in-differences methodology, we find a greater decline in liquidity commonality of stocks that had high ownership by affected ETFs (relative to those with low ownership). These results are robust to the exclusion of stocks that faced short-sale restrictions and trading halts on that day. We also conduct two falsification tests to further confirm that our results are not spurious. First, we use a pseudo-event date of August 17, 2015 (the previous Monday) to show that hypothetical trading halts (occurring at the same time in the same ETFs as on August 24, 2015) are not associated with a significant decrease in commonality in liquidity. Second, to allay any concerns about a pseudo-event date not mirroring the actual event date, we conduct a simulation analysis using the actual date. For this purpose, we randomize which ETFs are affected by the trading halts and also randomize the duration of the halts on the selected ETFs. In a spirit similar to the first falsification test, we do not observe a significant decrease in commonality in liquidity when we use the randomized trading halts. Keeping in mind the caveat that it is always challenging to isolate an effect using an extreme event when several confounding factors maybe at play, our results are suggestive of the notion that the arbitrage channel drives the relation between ETF ownership and commonality in liquidity.

As discussed above, an important innovation of ETFs is that they provide investors and arbitrageurs with the ability to engage in intraday trading. We take advantage of this feature of ETFs when we use the natural experiment of ETF trading halts over the course of the August 24, 2015 trading day. However, we refrain from using intraday data for the rest of the empirical analysis due to several reasons. First, to capture the intraday deviations between the prices of ETFs and their underlying securities, one would need the Intraday Indicative Values (IIVs) that ETFs disseminate to the markets but these are not available on commercial databases (e.g. TAQ). Moreover there is a computational trade-off between analyzing highly granular data over a short period versus relatively coarse data over a long period (notably, such a tradeoff favors intraday analysis of the extraordinary events of August 24, 2015). Second, conducting the analysis at the daily level allows us to compare and contrast our findings with those for actively managed open-end funds for which we can only observe end-of-day pricing.

The remainder of the paper is structured as follows: section 1 reviews the related literature and highlights our contributions to it; section 2 presents the data and empirical methodology; section 3 examines the relation between commonality in liquidity and ETF ownership; section 4 establishes a causal interpretation of that relation using the reconstitution of the Russell 1000 and Russell 2000 indexes; 5 investigates the arbitrage mechanism in ETFs and how it contributes to the commonality in liquidity; section 6 uses ETF trading halts that occurred on August 24, 2015 to further identify the arbitrage channel driving the commonality in liquidity due to ETF ownership. Finally, section 7 concludes.

1. Literature Review and Our Contribution

Our paper contributes to several broad strands of the literature. First, we build on the recent research studying the impact that financial innovation has on capital markets. There is a growing literature that studies how the creation of new products can affect other related securities. Prior literature documents that ETFs affect the underlying securities' (i) by increasing their non-fundamental volatility (Malamud, 2015; Ben-David et al., 2018);[2] (ii) by increasing their co-movement in returns (Da and Shive (2017) and Israeli et al. (2017)); and (iii) informational efficiency (see Israeli et al. (2017) for a negative effect using all equity

[2]Malamud (2015) finds that introducing multiple ETFs can attenuate the effect that individual ETFs have on increasing the non-fundamental volatility.

ETFs; and see Glosten, Nallareddy, and Zou (2017) and Huang et al. (2018) for a positive effect using stocks trading in weak information environments and stocks belonging to industry ETFs, respectively). In addition, a number of papers have highlighted the effect of ETFs (or similar stock basket and index products) on the underlying securities' liquidity. Theoretical models by Subrahmanyam (1991) and Gorton and Pennacchi (1993) demonstrate that uninformed traders can benefit from trading "basket" (or "composite") securities (e.g. mortgage-backed securities, index futures, closed-end mutual funds, and real estate investment trusts) in lieu of trading directly in the underlying securities. Specifically, they show that uninformed traders will migrate towards the "basket" where they will face fewer losses to informed traders. Therefore, a prediction of these theoretical models is that participation by uninformed liquidity traders and liquidity levels in the underlying securities will be affected. Empirical support for these predictions can be found in Hamm (2010) and Israeli et al. (2017) for stock ETFs and in Dannhauser (2017) for corporate bond ETFs. Results from several other studies show that the relation between ETF ownership and the liquidity of the underlying stocks is more nuanced. For instance, Nam (2017) shows that, conditional on the liquidity of the underlying securities, there is a differential impact of the ETF ownership on the underlying securities. Furthermore, Evans, Moussawi, Pagano, and Sedunov (2018) find that the impact of ETF ownership on the liquidity of underlying stocks is weaker when APs delay arbitrage through share creation and redemption activities. Our paper contributes to this literature by being the first study to examine the impact of ETFs on the commonality in liquidity of the underlying securities in the ETF basket, rather than the level of liquidity. This in turn has implications for market fragility to the extent that higher commonality in liquidity adversely affects the ability of investors to diversify liquidity shocks. In this context our paper also contributes to the recent work showing that information linkages and liquidity mismatches between the ETF and the constituent securities can increase market fragility (see Bhattacharya and O'Hara (2016) and Pan and Zeng (2017), respectively).

Second, in addition to contributing to the literature on the impact of ETFs on their underlying securities, we shed light on the factors that affect the commonality in liquidity of securities. The asset pricing literature has long recognized the role of liquidity in explaining the cross-sectional variation in expected returns of securities (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996). Subsequently, a number of papers provide evidence that investors demand a higher expected return for assets that exhibit more commonality in liquidity, i.e., assets whose liquidity co-moves more with systematic liquidity (Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005). Several explanations have been advanced for why commonality in liquidity arises in the first place. These explanations can be largely categorized into supply-side and demand-side sources of commonality in liquidity. On the supply side, Coughenour and Saad (2004) show that liquidity of stocks handled by the same specialist firm co-moves in response to a funding shock faced by the specialist. More generally, Brunnermeier and Pedersen (2009) and Hameed et al. (2010) argue that financial intermediaries, who provide liquidity across assets, can simultaneously experience tightening funding constraints. In response to a common funding shock, intermediaries will reduce the supply of liquidity across assets giving rise to commonality in liquidity.

On the demand side, it has been shown that commonality in liquidity is driven by correlated trading activity due to (i) investors (Chordia et al., 2000; Hasbrouck and Seppi, 2001), (ii) institutional ownership (Kamara et al., 2008; Koch et al., 2016), and (iii) arbitrageurs (Corwin and Lipson, 2011; Tomio, 2017). Karolyi, Lee, and van Dijk (2012) assess the relative importance of the two competing explanations (supply- and demand-side) of commonality in liquidity using an international setting and find stronger support for the demand-side explanation. Our paper contributes to the literature on the demand-side explanation by showing that the arbitrage mechanism in ETFs generates simultaneous demand for the underlying securities in the ETF basket which in turn affects the commonality in liquidity of the securities. Our findings therefore complement the findings from earlier literature that relies on correlated flows or correlated information to induce simultaneous trading across securities held by open-end mutual funds (Koch et al., 2016). In contrast to Koch et al. (2016) where the correlated trading of mutual funds owning the stocks drives the commonality, our study shows that trading by other market participants including arbitrageurs rather than the trading by ETFs themselves affects the commonality in liquidity.

2. Data and Methodology

2.1. Sample

We start by identifying all ETFs traded on major US stock exchanges from CRSP and Compustat. In CRSP we use the historical share code 73, which exclusively defines ETFs. We then augment our sample from Compustat where we identify ETFs using the security-type variables. Starting with a sample of 2,445 ETFs, we exclude commodities, futures-based, levered, inverse, fixed-income, and international equity ETFs from our sample. Therefore, we focus on the ETFs that are broad-, sector-, and style-based ETFs that physically own US stocks. This process generates the initial sample which consists of 1,294 unique ETFs between January 1, 2000 and December 31, 2016.[3] The overall market capitalization of the sample ETFs with holdings data is approximately $1.25 trillion or about 93% of the assets under management (AUM) of all US-listed US equity ETFs, as of December 31, 2015. This suggests that our sample is comprehensive.

Similar to mutual funds, most ETFs are registered funds under the Investment Company Act of 1940

[3] We start our sample on January 1, 2000 because iShares entered the ETF market that year and very few ETFs existed prior to that date.

and are consequently required to report their quarterly portfolio holdings.[4] We collect the portfolio holdings for each identified ETF using the Thomson Reuters Mutual Fund Holding Database, which we match to the CRSP Mutual Fund Database. We supplement the holdings data using the CRSP Mutual Fund Database after 2010 in order to match as many US Equity ETFs as possible to their equity holdings during our sample period. For each stock in the CRSP stock file universe, we construct the ETF ownership at the end of each calendar quarter by aligning the ownership of ETFs with different reporting fiscal period-end using the following methodology. For each stock i in a given calendar quarter end q, we compute the ETF Ownership ($ETFOWN$) as:

$$ETFOWN_{i,q} = \frac{\sum_j w_j \times MKTCAP_j}{MKTCAP_i} \tag{1}$$

where w_j is computed as the portfolio weight of ETF j in stock i, using the most recent quarterly holding report disclosed by the ETF in the Thomson Reuters Mutual Fund Holding database. $MKTCAP_j$ and $MKTCAP_i$ are the updated market capitalization of ETF j and of stock i, respectively, at the end of a calendar quarter. We compute $MKTCAP_j$ as the product of the ETF price (available from CRSP) and shares outstanding (available from Bloomberg).[5] While w_j is computed from the most recent quarterly investment company report (at fiscal quarter end), $w_j \times MKTCAP_j$ reflects the dollar ownership of ETF j in stock i updated to the current month. To handle the special cases where a fund family offers both ETF and open-end mutual fund share classes (e.g., Vanguard and Pax World Management), we use the fractional total assets of the ETF share class to impute the proportional holdings in each stock attributable to the ETF share class.

Since ownership of other institutional investors can influence the commonality in liquidity, we control for the percent ownership of non-ETF index and active mutual funds. We identify index funds using both the index fund flag and the fund names in the CRSP Mutual Fund Database, and classify all other mutual funds as active. Ownership data for non-mutual fund investors for each company is from Thomson Reuters Institutional Ownership Database.

The resulting sample consists of 324,443 stock-quarter observations over the period from January 1, 2000 to December 31, 2016.

[4] Active ETFs are required to report their holdings daily; whereas passive ETFs are not subject to the daily reporting requirement. DTCC and ETF Global provide daily holdings on ETFs starting in 2008. We nonetheless maintain the analysis at the quarterly level because (a) we necessitate an estimation window to estimate our commonality in liquidity measure, which uses daily observations; (b) our ability to extend the analysis for 8 more years prior to 2008; and (c) maintain the ETF coverage to the universe of US-listed ETFs holding US stocks.

[5] Due to daily creation and redemption, the total shares outstanding of an ETF change on a daily basis, and we therefore obtain updated information from Bloomberg, since this data is not reported accurately in CRSP and Compustat according to Ben-David et al. (2018).

2.2. Commonality in Liquidity Measure

We construct our commonality in liquidity measure based on the approach used in Coughenour and Saad (2004) and Koch et al. (2016). Coughenour and Saad (2004) study how a stock's liquidity co-moves with the liquidity of other stocks handled by the same specialist firm, whereas Koch et al. (2016) study the extent to which mutual fund ownership determines the co-movement in liquidity of stocks. The basic idea behind the Koch et al. (2016) measure is that the more a stock is owned by mutual funds, the more its changes in liquidity should co-move with those of other stocks that also have high mutual fund ownership. Our measure uses the same intuition with the focus being on ETF ownership instead of mutual fund ownership.

We follow Kamara et al. (2008) and Koch et al. (2016) in selecting the Amihud (2002) liquidity measure as our proxy for liquidity because it can easily be estimated from daily data and performs well relative to intra-day measures of liquidity (Hasbrouck, 2009; Goyenko, Holden, and Trzcinka, 2009). Moreover, consistent with prior studies, we focus on changes as opposed to levels to reduce potential econometric issues such as non-stationarity (Chordia et al., 2000; Kamara et al., 2008; Koch et al., 2016; Karolyi et al., 2012).

Specifically, for each stock i on day d, we calculate the changes in the Amihud (2002) illiquidity measure for all ordinary common shares in CRSP (share code of 10 and 11) with stock prices greater than \$2 (as in Chordia et al. (2000) and Kamara et al. (2008) among others) as follows:

$$\Delta illiq_{i,d} \equiv log\left[\frac{|R_{i,d}|}{P_{i,d} \times Volume_{i,d}} \Big/ \frac{|R_{i,d-1}|}{P_{i,d-1} \times Volume_{i,d-1}}\right] \tag{2}$$

where $R_{i,d}$, $P_{i,d}$, and $Volume_{i,d}$ are the CRSP return, price, and trading volume, on stock i on day d. We require the returns to be non-missing and the dollar volume to be strictly positive and non-missing (the results are not sensitive when we modify the Amihud measure by adding one to it to include zero return cases). To minimize the impact of outliers, we take the difference in the logs of the Amihud (2002) illiquidity measure between day d and day $d-1$ and we further winsorize the final measure at the 1% and 99% percentiles.

We then estimate the following regression for each stock i in calendar quarter q:

$$\begin{aligned}\Delta illiq_{i,q,d} = \alpha &+ \beta^{-1}_{HighETF,i,q}\Delta illiq_{HighETF,q,d-1} + \beta^{0}_{HighETF,i,q}\Delta illiq_{HighETF,q,d} \\ &+ \beta^{+1}_{HighETF,i,q}\Delta illiq_{HighETF,q,d+1} + \beta^{-1}_{m,i,q}\Delta illiq_{m,q,d-1} + \beta^{0}_{m,i,q}\Delta illiq_{m,q,d} \\ &+ \beta^{+1}_{m,i,q}\Delta illiq_{m,q,d+1} + \beta^{0}_{mret,i,q}R_{m,q,d} + \beta^{-1}_{mret,i,q}R_{m,q,d-1} \\ &+ \beta^{+1}_{mret,i,q}R_{m,q,d+1} + \beta_{iret,i,q}R^2_{i,q,d} + \epsilon_{i,q,d}\end{aligned} \tag{3}$$

where $\Delta illiq_{i,q,d}$ is the daily change in illiquidity of stock i within the calendar quarter q estimated using Equation 2. $\Delta illiq_{HighETF,q,d}$ is the daily change in illiquidity on a value-weighted basket of stocks in the top quartile of ETF ownership each quarter after excluding stock i. $\Delta illiq_{m,q,d}$ is the daily change in market illiquidity where market illiquidity is calculated as the value-weighted average illiquidity of all CRSP stocks in day d excluding stock i. Similar to Koch et al. (2016), we also include the lag and lead of the changes in illiquidity of the stocks with High ETF ownership as well as the lag and lead of the changes in market illiquidity. We also include the lag, contemporaneous, and lead of the value-weighted CRSP market return, and the contemporaneous squared stock i return.

We use the contemporaneous $\beta^0_{HighETF}$ as our main measure of commonality in liquidity with high ETF ownership stocks. However, our results are qualitatively similar if we use the sum of the lag, contemporaneous, and lead coefficients in our analysis. Table 1 provides summary statistics on $\beta^0_{HighETF}$ which we refer to as simply $\beta_{HighETF}$ in the rest of the paper.

3. Commonality in Liquidity and ETF Ownership

3.1. Baseline Results

Our main hypothesis is that ETFs increase the commonality of liquidity of the underlying basket of securities they hold. Consequently, a security that has higher levels of ETF ownership will exhibit higher commonality in liquidity. We conduct an initial test of this hypothesis by first regressing the commonality in liquidity measure ($\beta_{HighETF}$) on lagged ETF ownership ($ETFOWN$). We then subsequently introduce other independent variables in the regression. Our endeavor is to determine whether the relation between $\beta_{HighETF}$ and $ETFOWN$ is a result of ETF ownership or of other institutional ownership which happens to be correlated with ETF ownership. Therefore, we include the lagged passive mutual fund ownership ($INXOWN$), lagged active mutual fund ownership ($MFOWN$), and lagged ownership by other institutional investors, i.e., hedge funds, independent advisors, trusts, insurance companies, endowments, pension funds, and other institutional accounts ($OTHROWN$). Each ownership variable is standardized prior to their inclusion in the model by demeaning the cross-sectional mean and dividing by the standard deviation. The comprehensive specification is as follows:

$$\begin{aligned}\beta_{HighETF,i,q} = \gamma_0 + \gamma_1 ETFOWN_{i,q-1} + \gamma_2 INXOWN_{i,q-1} + \gamma_3 MFOWN_{i,q-1} + \gamma_4 OTHROWN_{i,q-1} \\ + CONTROLS_{i,q-1} + \epsilon_{i,q} \quad (4)\end{aligned}$$

In all the specifications, we control for the logarithm of the market capitalization of the firm ($SIZE$) and the liquidity level of the stock using the Amihud (2002) illiquidity measure ($AMIHUD$). These controls aim to address the concern that firm size and stock liquidity characteristics determine both commonality and their selection into ETF baskets. Additionally, we use stock and quarter fixed effects and double-cluster the standard errors at the stock and quarter level to adjust for both serial- and cross-correlation.

Table 2, Panel A reports the results. Model 1, is a regression of $\beta_{HighETF}$ on $ETFOWN$. The coefficient on $ETFOWN$ of 0.0660 is positive and significant at the 1% level. Since we use standardized measures of ownership, this implies that a one standard deviation in ETF ownership (2.94%, see Table 1) is associated with a 6.60% increase in the commonality in liquidity.[6] Models 2 to 4 control for ownership of other institutional investors including index funds ($INXOWN$), open-end mutual funds ($MFOWN$), and others ($OTHROWN$). Both the ownership of index funds and open-end mutual funds are significantly related to commonality in liquidity (see Models 2 and 3). Note that it would be unfair to compare the effects of different institutions with each other considering that the commonality in liquidity measure is constructed with stocks that are in the top quartile of ETF ownership. More importantly, even after controlling for the ownership of other institutions, the effect of ETF ownership remains statistically significant with little impact on its economic magnitude.

In Table 2, Panel B we include additional controls. In Model 1, we repeat the baseline results in Panel A for comparison; in Model 2, we control for the stock's co-movement of returns with the market returns that exclude the given stock (β_{mxs}) and for the lagged beta on the aggregate market illiquidity (β_m). Da and Shive (2017) find that ETFs increase the co-movement in returns of their underlying basket of stocks. To the extent that commonality in liquidity is related to commonality in returns, our results might be picking up the latter (Karolyi et al., 2012). Model 2 shows that there is indeed a positive and significant relation between commonality in liquidity and commonality in returns. However, our main variable of interest in the regression, $ETFOWN$, continues to be positive and significant in the same magnitudes as before. In Model 3, we add the lagged value of the commonality in liquidity measure, $\beta_{HighETF}$, to control for significant autocorrelation in the measure (the AR(1) coefficient is 0.0362). Although the lagged measure is not significant perhaps because of other controls, $ETFOWN$ continues to be significantly positive as in our earlier specifications. In Model 4, we additionally include the lagged value of the Koch et al. (2016) commonality in liquidity with respect to stocks that have high mutual fund ownership, β_{HighMF}, which is the active mutual fund analog to the $\beta_{HighETF}$ measure we study. The inclusion of that variable does not appear to qualitatively change the results.[7] To assess whether our analysis is robust to alternative measures

[6]We observe high economic significance even when we use unstandardized measures of ownership. A one percentage point increase in the ETF ownership is associated with a 5.41% increase in the commonality in liquidity (See Table IA.1 in the Internet Appendix).

[7]In unreported tests we also exclude stock fixed effects in all Panel B specifications. The results remain similar, suggesting that the relation between the ETF ownership and liquidity commonality of a stock not only holds within the stocks but also

of stock liquidity, we also repeat our analysis using bid-ask spreads instead of using the Amihud (2002) illiquidity measure. Our results reported in Panels A and B of Table IA.2 are qualitatively similar to the findings in Table 2.

Taken together, the results support our conjecture that (a) there is a significant correlation between ETF ownership and liquidity commonality; (b) the effect does not appear to be an indexing phenomenon as the inclusion of index fund ownership does not change the main finding; and (c) the relation between ETF ownership and liquidity commonality is distinct from and in addition to the previously documented relation between mutual fund ownership and commonality in liquidity (Koch et al., 2016).

3.2. Are the Results Driven by Index Membership and the Crisis Period?

It is possible that the relation between ETF ownership and liquidity commonality is driven by small capitalization stocks even after controlling for their lower liquidity levels. Additionally, it is also conceivable that this relation is confined to stocks belonging to certain popular indexes that ETFs track. We examine this possibility by separately estimating the baseline models on stocks that are part of the Russell 3000, the Russell 2000, and the S&P 500. The Russell 3000 index includes the 3000 largest publicly held US companies based on market capitalization. The Russell 2000 index includes the smallest 2000 companies belonging to the Russell 3000. The S&P 500 index includes 500 of the largest US companies by market capitalization. In contrast to the Russell indexes, S&P 500 members are not solely chosen on the basis of market capitalization. The other criteria are that at least 50% of the company's shares outstanding are available for trading; the company's as-reported earnings over the most recent quarter, as well as over the year, must be positive; and that the company's shares have active and deep markets. As of March 2016, the average (median) market capitalization for the Russell 3000, Russell 2000, and S&P 500 was $110 billion ($1.1 billion), $1.8 billion ($0.6 billion), and $35.2 billion ($17 billion), respectively.

We report the results in Table 3. Model 1 reiterates the baseline results for comparison. Models 2 through 4 report the baseline model for the Russell 3000, Russell 2000, and S&P 500 index member stocks, respectively. As an additional control for ownership effects of other stock basket and related index products, we include the weight of the stock in the index.

The coefficients on $ETFOWN$ remain positive and significant in all the sub-samples. The magnitude of the $ETFOWN$ coefficient appears stable across the different indexes. The effect is slightly weaker for the smaller capitalized Russell 2000 stocks as compared to the Russell 3000 stocks. Moreover, the magnitude of the coefficient is the largest for the larger S&P 500 stocks.

across stocks. Moreover, in Models 3 and 4 we also estimate a dynamic panel regression with the Arellano and Bond (1991) correction and find similar results.

We next examine whether the relation between ETF ownership and commonality in liquidity is driven by the crisis period. To do so, we reestimate the baseline model excluding the crisis period 2007–2009. Table 4 reports the results from Model 2. Again, Model 1 presents the results of the baseline specification for comparison. The coefficient on $ETFOWN$ in the sample excluding the crisis period is 0.0566 compared to 0.0584 for the entire period, and is statistically significant at the 1% level.

Collectively, these results do not support the conjecture that stock size, or index membership, or the crisis period drives the observed relation between the ETF ownership and commonality in liquidity.

3.3. Pairwise Correlation in Liquidity of Stocks with Common ETF Ownership

In this section, we use an alternative approach to examine the impact on liquidity co-movement of stocks when they are connected to each other by virtue of being held by the same ETF. For this purpose, we adopt the methodology in Antón and Polk (2014) to estimate the common ETF ownership between any two given stocks in a given quarter.

There are both pros and cons of using the pairwise correlation methodology relative to our earlier approach that relies on using a two-step procedure that involves first estimating $\beta_{HighETF}$ using a "market model" of liquidity, and then relating it to the overall ETF ownership. On one hand, pairwise correlation approach offers the advantage of not requiring a specific model to estimate the co-movement in liquidity of two stocks. Instead, in this approach, we include stock $\times$ time fixed effects to capture the time-series variation in the correlation between the liquidity of a stock and marketwide liquidity (in addition to other time-varying stock characteristics). On the other hand, a pairwise correlation approach ignores the effect of correlated liquidity shocks of various ETFs that own different stocks, which can lead to co-movement in liquidity without the presence of common ownership (Greenwood and Thesmar, 2011). While correlated flows can coincide with common ownership due to, for example, correlated flows into certain style or sector ETFs that own similar basket of stocks, it is not always the case. In the subsequent section, we report evidence on both the correlated trading through arbitrage trading, and on correlated liquidity shocks which translate in higher absolute flows and flow volatility, both of which give rise to liquidity co-movement. Therefore, we view the two approaches as complementary to each other.

To implement the pairwise correlation approach, in a given quarter q, we identify all the stock pair combinations and for each stock-pair ij, we compute the common ownership measure $ETFFCAP_{ij,q}$ as the total dollar value held by the F common ETFs, scaled by the sum of market capitalizations of the two stocks.

$$ETFFCAP_{ij,q} = \frac{\sum_{f=1}^{F} S_{i,q}^{f} P_{i,q} + S_{j,q}^{f} P_{j,q}}{S_{i,q} P_{i,q} + S_{j,q} P_{j,q}} \tag{5}$$

Analogously, to control for the effects of other common ownership held by other institutions on the commonality in liquidity, we compute $MFFCAP_{ij,q}$ and $INXFCAP_{ij,q}$, the common ownership held by active mutual funds and index mutual funds, respectively. Furthermore, to facilitate cross-sectional comparisons across the different institution types, we standardize the $FCAP$ measures to have a mean of zero and a standard deviation of one. Next, we estimate the effect of common ownership of different institutions in quarter $q-1$ on the correlation of changes in the Amihud (2002) liquidity of each stock pair over the quarter q. Specifically, we estimate the following regression using all the correlations between all stock pairs in each quarter for our sample period, resulting in $550,299,832$ stock-pair-quarter observations.

$$\rho_{ij,q} = \lambda_0 + \lambda_1 ETFFCAP_{ij,q-1} + \lambda_2 MFFCAP_{ij,q-1} + \lambda_3 INXFCAP_{ij,q-1} + CONTROLS_{ij,q-1} + \epsilon_{ij,q} \quad (6)$$

where $\rho_{ij,q}$ is the pairwise correlation between the daily change in Amihud (2002) liquidity of stock i and that of stock j estimated over each quarter q.

We add stock-quarter fixed effects for both stocks i and j to control for unobservable time-varying characteristics of each stock in the pair that can potentially affect the correlation in the changes in liquidity of the two stocks. Note that it is not possible to include the stock pair ij fixed-effects in the above regression as it would subsume the common ownership effect. To determine statistical significance, we triple-cluster the standard errors at the quarter, stock i, and stock j level.

Table 5, Panel A, reports the results from the estimation in Equation 6. Since two stocks can be connected by virtue of being jointly held by different types of institutions (active and passive mutual funds as well as ETFs), to compare and contrast the effect of each type of institutional ownership on the commonality in stock liquidity, we first look at their effects individually in Models 1 through 3.[8]

In Model 1, we observe a positive and significant coefficient of 0.0126 on $ETFFCAP$, which suggests that when an ETF holds a larger position in two stocks, it is associated with an increase in commonality in the liquidity of those stocks. In Model 2, we examine the individual effect of the $INXFCAP$ measure on the commonality in liquidity. We find a positive and significant coefficient of 0.0087. We next examine the effect of $MFFCAP$ on its own in Model 3, and find here again a positive and significant coefficient of 0.0081 on the stock pairwise correlation in liquidity, which corroborates the results in Koch et al. (2016) that active mutual fund ownership also acts to increase commonality in liquidity among the stocks held by these

[8]Note that in this analysis, we exclude the ownership of other institutions due to non-availability of this data at the fund level. Recall that previously we inferred the ownership of all other institutions by subtracting the ownership of ETFs, active and passive mutual funds from the total institutional ownership in the 13F data reported at the parent institution level (e.g., Fidelity Management). That methodology was appropriate for our earlier stock-level analysis where we did not necessitate fund-level ownership to determine the connectedness of two stocks. It is not feasible to infer the ownership of other institutions at the fund level since there is no mapping between the parent institution in the 13F data and the mutual funds belonging to this parent institution (e.g., Fidelity Management vs. Fidelity Contrafund Fund).

institutions.

In Model 4, we proceed to examine the combined effects of all three $FCAP$ measures on commonality in liquidity. We continue to find that the $FCAP$ measure for all three types of institutional ownership remains positive and significant with a coefficient of 0.0071, 0.0023, and 0.0053 for $ETFFCAP$, $INXFCAP$, and $MFFCAP$, respectively. In Model 5, we control for the correlation in returns between the two stocks i and j ($\rho_{returns}$) calculated over the previous quarter. Antón and Polk (2014) find that stocks that are connected through common ownership exhibit higher return correlations and furthermore Avramov, Chordia, and Goyal (2006) find that return correlations are related to liquidity measures. We find a positive and significant coefficient of 0.0387 on $\rho_{returns}$, which suggests that higher correlation in returns also contributes to an increase in the correlation in liquidity. More importantly, after allowing for the effect of correlation in returns, the main coefficient of interest on $ETFFCAP$ remains positive (0.0064) and significant at the 1% level.

In Table 5, Panel B, we repeat the analysis in Panel A by using the number of ETFs that have common ownership of each stock pair instead of the percentage common ownership in these stocks. Specifically, we use the logarithm of one plus the number of ETFs that are common among the two stocks ($ETFNUM$) and examine the effect of that measure on the correlation in liquidity of each pair of stocks i and j. We also include as controls, the analogous measures for passive and active mutual funds ($INXNUM$ and $MFNUM$, respectively). $ETFNUM$ captures a different attribute of common ETF ownership of stocks, i.e. the number of common ETFs that hold a pair of stocks in contrast to $ETFFCAP$ that captures how much common ETFs together hold a pair of stocks.

As before, we first estimate the individual effects of each institution type in Models 1 through 3, and then their combined effect in Models 4 and 5. We again find that there is greater correlation in liquidity of the stocks that are connected to each other on account of a larger number of ETFs holding them regardless of whether we control for the common ownership of other institutions and return correlation (see Models 1, 4, and 5). This finding is also economically large. Based on the most comprehensive specification in Model 5, a one standard deviation (10.6, see Table 1) increase in the number of ETFs that hold the same pair of stocks is associated with an increase of $log(1 + 10.06) \times 0.01737 = 4.2\%$ increase in pairwise liquidity co-movement, which is about 23% of one standard deviation (18.06%; see Table 1 of pairwise correlation in liquidity). The results for the effect of other institution types are largely similar except that the effect of index mutual fund ownership becomes insignificant in Model 5.

Taken together, the evidence in this section indicates that there is a strong effect of ETFs jointly holding a pair of stocks on the correlation in the liquidity of those stocks, and this effect is distinct from that of other institutions.

4. Establishing Causality between Commonality in Liquidity and ETF Ownership

In this section, we conduct additional analyses using the Russell indexes reconstitution experiment which allows us to exploit plausibly exogenous changes in ETF ownership and consequently in common ETF ownership around reconstitution events in order to establish a causal relation between ETF common ownership and the co-movement in liquidity of these connected stocks (as opposed to ETFs endogenously choosing to invest in stocks that exhibit similar characteristics, and therefore higher co-movement in liquidity).

Several recent papers have used the reconstitution of the Russell indexes as a source of plausibly exogenous variation in the stock holdings of passive investors (see for example, Chang, Hong, and Liskovich, 2015; Boone and White, 2015; Appel et al., 2016; Ben-David et al., 2018; Cao, Gustafson, and Velthuis, 2018, among others). The Russell 1000 and 2000 stock indexes comprise the first 1,000 and next 2,000 largest stocks ranked by market capitalization, respectively. Moreover, Russell Inc. reconstitutes the indexes on the last Friday of June every year, based only on end-of-May stock capitalization with typically no discretion involved in index assignment. Once the index composition, is determined it remains constant for the rest of the year. For stocks in a close neighborhood of the cutoff, changes in index membership are random events, once we control for the assignment variable, namely, market capitalization, because they result from random variation in stock prices at the end of May. However, the resulting index reassignment has a large effect on ownership of ETFs that track either of the two indexes. For example, consider a stock ranked at the bottom of the Russell 1000. As its market capitalization is small relative to the other stocks in the index, Russell 1000 ETFs allocate it a low weight in their portfolios. However, small random fluctuations in its market capitalization rank relative to that of other firms can cause it to be reassigned to the Russell 2000. This in turn would require Russell 2000 ETFs to take a significant position in this stock because it would now be one of the largest stocks in the index. Therefore, the Russell reconstitution experiment allows us to exploit mechanical changes in ETF ownership and consequently in common ETF ownership around reconstitution events in order to establish a causal relation between ETF common ownership and commonality in liquidity of stocks constituting the ETF portfolio.

Intuitively, when one stock is reassigned from one Russell index to the other, the liquidity of that stock should co-move more with the liquidity of other stocks in the new index, and conversely, should co-move less with the liquidity of stocks remaining in the old index, if common ETF ownership drives the co-movement in liquidity.

Following this logic, we regress the correlation in changes in Amihud (2002) liquidity between two stocks i and j ($\rho_{\Delta liquidity}$) on the degree to which those two stocks are connected through common ETF ownership

$ETFFCAP$ and the interaction of $ETFFCAP$ with an indicator variable, $SWITCH$, determining the reassignment of one of the stocks in the Russell indexes. There are several possibilities related to the switches between indexes: both stocks i and j could be reassigned from the Russell 1000 to the Russell 2000 ($SWITCH_A$), stock i could have switched into the Russell 2000 and out of the Russell 1000 whereas the other stock j remained in the Russell 2000 ($SWITCH_B$), both stocks i and j could have been reassigned from the Russell 2000 to the Russell 1000 ($SWITCH_C$), and finally, one of the stocks could have switched into the Russell 1000 and out of the Russell 2000 whereas the other remained in the Russell 2000 ($SWITCH_D$). The indicator variables $SWITCH_A$, $SWITCH_B$, $SWITCH_C$, and $SWITCH_D$ take on the value 1 if the corresponding event is true, and 0 otherwise. The fact that we also examine the switch cases where only one stock in the pair moves from one index to the other should alleviate potential concerns about any pre-existing return co-movement between the stock pair affecting our interpretation. Moreover, we explicitly control for prior return co-movement in the stocks across all types of switches.

The sample composition and switch indicator variables remain constant for all the months between July, the first month after index reconstitution, and May of the next year. Following Appel et al. (2016) and Ben-David et al. (2018), we end our sample period in the first quarter of 2007, since starting in June 2007, Russell implemented a "banding" rule in which stocks near the cutoff would not switch indexes unless the change in their relative size ranking was sufficiently large, which will affect the reconstitution process.

Specifically, we estimate the following regression over the period starting in January 2000 and ending in March 2007:

$$\begin{aligned}\rho_{ij,q} = \lambda_0 + \lambda_1 ETFFCAP_{ij,q-1} + \lambda_2 ETFFCAP_{ij,q-1} \times SWITCH + \\ \lambda_3 MFFCAP_{ij,q-1} + \lambda_4 MFFCAP_{ij,q-1} \times SWITCH + \\ \lambda_5 INXFCAP_{ij,q-1} + \lambda_6 INXFCAP_{ij,q-1} \times SWITCH + CONTROLS_{ij,q-1} + \epsilon_{ij,q} \end{aligned} \quad (7)$$

where $\rho_{ij,q}$ is the pairwise correlation between the change in Amihud (2002) liquidity of stock i and that of stock j estimated over each quarter q.

We add quarter fixed effects and stock fixed effects for both stocks i and j to control for unobservable factors that can potentially affect the correlation in the changes in liquidity of the two stocks. The inclusion of quarter fixed effects also controls for the end-of-May market capitalization of the two stocks to control for the factor that determines their inclusion in the index as in Appel et al. (2016). As before, we also include the past correlation in returns ($\rho_{returns}$) of the two stocks to control for its effect on the commonality in liquidity. Finally, to determine statistical significance, we triple-cluster the standard errors at the quarter, stock i, and stock j level.

Table 6 reports the results for the estimation of Equation 7. In Panel A, we use a sample consisting of the pairwise combinations of 100 stocks on either side of the market capitalization cutoff between the Russell 1000 and Russell 2000 indexes (i.e., the 100 lowest stocks, and 100 highest stocks by market capitalization, in the Russell 1000 and 2000 indexes, respectively). In Panel B, we augment the sample to have a cutoff of 200 stocks around the Russell 1000 and 2000 index boundary.[9]

Focusing on the 100 stock cutoff in Panel A, we find that when two stocks are both reassigned to the Russell 2000 from the Russell 1000 (Model 1), the interaction of $ETFFCAP$ with the switch indicator variable, $SWITCH_A$, is positive (consistent with an exogenous increase in the ETF ownership of a switch from Russell 1000 to Russell 2000) though not statistically significant. However, when one of the two stocks is reassigned to the Russell 2000, the co-movement in changes in liquidity with all the other stocks in the Russell 2000 increases substantially. The coefficient on the interaction of $ETFFCAP$ and $SWITCH_B$ is positive 0.0080 and statistically significant at the 1% level. In Model 3, we examine the case where both stocks are reassigned to the Russell 2000 from the Russell 1000. In this case we find that the coefficient on the interaction between $ETFFCAP$ and the switch variable $SWITCH_C$ is -0.0080, which is negative and statistically significant at the 5% level. Recall that a move from the Russell 2000 to the Russell 1000 represents an exogenous drop in the ETF ownership of stocks. Model 4 reports the findings for the case where one stock is reassigned to the Russell 1000 but the other stock in the pair is not. In that case we find that the co-movement in liquidity between the two stocks decreases as the coefficient on $ETFFCAP$ interacted with $SWITCH_D$ is negative but not statistically significant.

Results in Panel A appear to suffer from low statistical power as there are very few stocks (40 on average) that switch within the cutoff of 100 stocks on either side of the boundary between the Russell 1000 and Russell 2000 indexes. Therefore, in Panel B, we increase the cutoff to 200 stocks. We now find that when either both stocks, or only one stock, switch from the Russell 1000 to the Russell 2000, the resulting exogenous increase in common ETF ownership causes them to have higher co-movement in their changes in liquidity (coefficients of 0.0048 and 0.0073 in Model 1 and Model 2, respectively, significant at the 5% level or better). As hypothesized, we find the opposite effect when both stocks, or only one of the stocks, switch from the Russell 2000 to the Russell 1000, consistent with the effect of an expected drop in the common ETF ownership (coefficients of -0.0072 and -0.0049 in Model 3 and Model 4, respectively, significant at the 5% level).

Reconstitution of Russell indexes can result in changes in the aggregate ETF ownership along with the

[9] In unreported results, we augment the sample cutoff to 500 stocks on either side of the Russell 1000 and 2000 index boundary, and find results that are qualitatively similar to the 200 stock cutoff.

changes in the common ETF ownership. Therefore, we also use an instrumental variable (IV) approach, similar to Appel et al. (2016) and Ben-David et al. (2018). The identification strategy relies on the fact that random shocks to stocks that are ranked near the 1000/2000 boundary can reshuffle them exogenously across indexes when the annual reconstitution takes place at the end of June. Therefore, the indicator variable, $SWITCH$, serves as an exogenous instrument for ETF ownership change. Using a two-stage least squares (2SLS) approach, we simultaneously estimate the effect of the switches between the Russell indexes (our IV) and the common ETF ownership (first stage), and the effect of the instrumented common ETF ownership on the co-movement in liquidity of stocks (second stage).

More formally, in the first stage, the $ETFFCAP$ measure of the common ETF ownership between any two given stocks is regressed on the log market capitalization of the first stock and of the second stock, both estimated at the end of May each year, before the index reconstitution, and a $SWITCH$ indicator variable. We verify the relevance condition for the IV through our first-stage estimations, and the exclusion restriction should hold as index inclusion should not be directly related to commonality in liquidity after controlling for the factor that determines index inclusion, i.e., stocks' end-of-May market capitalizations.[10]

Similar to the previous analysis, the $SWITCH$ variable differs according to the specification. To recapitulate, $SWITCH_A$ takes the value of 1 if both stocks switch from the Russell 1000 to 2000, and 0 otherwise. $SWITCH_B$ takes the value of 1 if one of the stocks switch into the Russell 2000 and the other remains in the Russell 2000, and 0 otherwise. $SWITCH_C$ takes the value of 1 if both stocks switch from the Russell 2000 to the Russell 1000, and 0 otherwise. $SWITCH_D$ takes the value of 1 if one of the stocks switches into the Russell 1000 and the other remains in the Russell 2000, and 0 otherwise. In the second stage, the correlation in the changes in Amihud (2002) liquidity between the two stocks ($\rho_{\Delta liquidity}$) is regressed against the predicted value of $ETFFCAP$ ($\widehat{ETFFCAP}$) and the log market capitalization of the first and second stock again estimated at the end of May each year.[11]

Table 7 reports the results. Panel A, uses a sample of 100 stocks on either side of the market capitalization cutoff between the Russell 1000 and Russell 2000 indexes (the 100 lowest stocks, and 100 highest stocks by market capitalization, in the Russell 1000 and 2000 indexes, respectively). Panel B, increases the cutoff to 200 stocks.

In Model 1, we find that as expected the $ETFFCAP$ measure between two stocks increases as both stocks move from the Russell 1000 to the Russell 2000 with a positive and significant coefficient on $SWITCH_A$ of 0.6628 in the first stage. In Model 2, we find that the predicted value of $ETFFCAP$ ($\widehat{ETFFCAP}$)

[10] For robustness, in an alternative specification we replace stocks' market capitalizations with their ranks in the index to also adjust for the float since there may be significant inside ownership in some stocks, which in turn could possibly affect the liquidity levels (Heflin and Shaw, 2000). Our results remain qualitatively similar.

[11] In an alternative specification, we additionally control for the $MFFCAP$ in the first stage to control for common ownership of stocks by open-end mutual funds, and find qualitatively similar results.

increases the co-movement in liquidity of the two stocks as we observe a positive and significant coefficient of 0.0204 on the predicted common ETF ownership in the second stage. Conversely, we find that when both stocks are reassigned to the Russell 1000 from the Russell 2000, the predicted $ETFFCAP$ is negatively and significantly related to the co-movement in liquidity of both stocks in the first stage (coefficients of -0.1016 on $SWITCH_C$ in Model 5, and and -0.3792 on $SWITCH_D$ in Model 7). Again, we observe that the predicted value of $ETFFCAP$ positively influences the co-movement in the liquidity of the stocks, though the relation is significant only in Model 8. The results are qualitatively similar when we increase the cutoff to 200 stocks on either side of the boundary between the Russell 1000 and Russell 2000 indexes. Note that these coefficients appear larger than those reported for the non-IV approach but the two cannot be compared as the IV approach captures the local effect of the instrumented variable.

Collectively, our findings in this section using the Russell 1000/2000 reconstitution as a quasi-natural experiment further corroborate our hypothesis of a causal relation between ETF ownership and liquidity commonality. In the next section, we explore whether the channels driving the relation between common ownership and co-movement in liquidity is also distinct in the case of ETFs. In particular, we examine the unique organizational structure of ETFs to study the role of the arbitrage process in influencing this relation.

5. ETF Ownership and Liquidity Commonality: Underlying Channels

ETFs are fundamentally different from other passive or active funds registered under the Investment Company Act of 1940 since they are traded on a secondary exchange concurrently with the underlying basket of securities they hold, thereby providing intraday liquidity to their investors.[12] Additionally, unlike open-end mutual funds, ETFs can be sold short. The concurrent trading of ETFs and the securities they hold presents the opportunity for market participants to uphold the law of one price. Therefore, continuously throughout the trading day, ETF prices are kept in line with the intrinsic value of the underlying securities through a process of arbitrage in which APs, as well as hedge funds and other institutional investors participate.

APs can engage in arbitrage activity by taking advantage of their ability to create and redeem ETF shares. If ETFs are trading at a premium relative to the net asset value (NAV) of their underlying securities, APs will buy the underlying securities while shorting the ETF in the secondary market until the two values equate. At the end of the trading day, the APs then deliver the underlying securities they accumulate during the day to the ETF sponsor in exchange for newly created ETF shares in the primary market. They then

[12] Closed-end mutual funds also trade on exchanges but the number of shares outstanding are generally fixed.

use these new shares to cover their ETF short positions. Conversely, if ETFs are trading at a discount relative to the underlying securities, the arbitrage process works in reverse: APs buy the ETF and short the underlying basket of securities during the trading day until the ETF price equates its intrinsic value. At the end of the trading day, the APs redeem the ETF shares they accumulate in exchange for the underlying basket. They then use the basket of securities they receive to cover their short positions. In contrast to arbitrage conducted by APs which happens in both the primary and secondary markets, hedge funds and other institutional investors conduct arbitrage exclusively in the secondary markets using rich/cheap convergence strategies. However, unlike APs, other market participants cannot directly cover their short positions in either the ETFs or the underlying securities by engaging in the creation or redemption of ETF shares but they can do so through agents or brokers who are APs in the designated ETFs (Ben-David et al., 2018).

We explore whether the ETF arbitrage mechanism, which differentiates ETFs from their open-end fund counterparts, is the source of the observed relation between the commonality in liquidity and ETF ownership. As described above, correlated demand of the constituent securities in the ETF basket can lead to simultaneous price impact on them, exacerbating the commonality in liquidity in these securities. Prior literature has used different proxies of arbitrage activity including the deviation between the ETF prices and the NAV of underlying securities (Ben-David et al., 2018) and ETF turnover (Da and Shive, 2017) as a single proxy is unlikely to be perfect. For instance, as pointed out in Brown, Davies, and Ringgenberg (2017), Da and Shive (2017), Tomio (2017), and Ben-David et al. (2018), a large deviation could also be due to the presence of limits of arbitrage. We recognize these challenges and propose several additional proxies of arbitrage activity, which employ the trading of the ETFs as well as the creation and redemption activities in the ETFs.

Our first proxy is the mispricing measure, i.e., the deviation between the ETF and the underlying basket prices. As argued in Ben-David et al. (2018), this measure signals arbitrage profitability, which should attract more arbitrageurs to engage in closing out the mispricing. We calculate mispricing as the sum of the absolute value of the daily difference between the ETF's end-of-the-day price and its end-of-the-day NAV (i.e., the ETF's discount or premium), aggregated over each quarter. We use the absolute value of the discount or premium because either a positive or a negative deviation from the NAV will offer opportunities for arbitrage. The discount or premium is generally referred to as the ETF's mispricing. We average the mispricing measure at the stock level using the ETF ownership in that stock as weights to create the variable $ETFAMISPRC$.

Precisely, for each stock i in calendar quarter q:

$$ETFAMISPRC_{i,q} = \sum_{j=1}^{J}\left[w_{j,q-1} \times \frac{1}{D}\sum_{d=1}^{D}\left|\frac{PRC_{j,d} - NAV_{j,d}}{PRC_{j,d}}\right|\right] \tag{8}$$

where $PRC_{j,d}$ and $NAV_{j,d}$ is the price and NAV of ETF j at the end of day d, respectively. J is the total number of ETFs that own a given stock i, and D is the number of days in a given quarter q. Finally, $w_{j,q-1}$ is the percent ownership of the ETF in a given stock i at the end of the previous quarter.

We use the end of the trading day as our unit of observation for ETF mispricing. However, since both ETFs and the component stocks trade simultaneously during the day, in principle, one could compute the average mispricing at the intraday level. In fact to facilitate arbitrage, ETFs disseminate the Intraday Indicative Value (IIV) of the underlying basket every 15 seconds and the most sophisticated arbitrageurs calculate their own IIVs at higher frequencies using proprietary models to circumvent stale prices. One can then match the traded prices of ETFs to their IIVs and calculate the mispricing every 15 seconds or even at shorter intervals. However, this task is made difficult by the fact that ETF IIVs are not stored on TAQ. To the extent that we use a daily mispricing measure, which is a weaker signal of arbitrage activity compared to a more refined one using intraday data, it should bias the analysis against finding significant results.

It is important to point that, in spite of arbitrage, substantial ETF mispricing can still exist. Petajisto (2017) estimates that deviations of 150 basis points exist on average between ETF prices and the basket's NAV. These deviations are larger for ETFs holding illiquid securities because the marginal cost of trading in the underlying nullifies the profits that would be earned through arbitrage. Therefore, it is conceivable that a given stock is part of an ETF which always exhibits a high mispricing. Our analysis controls for this possibility by including stock fixed-effects so that a stock's average ETF mispricing is taken into account.

Our second proxy of arbitrage activity is the standard deviation in the mispricing, $ETFSDMISPRC$, between the prices of the ETFs and the underlying securities. This measure addresses the aforementioned concern that the level of mispricing may reflect limits to arbitrage. The fact that ETF mispricing changes over time is suggestive of arbitrageurs being active in exploiting it. As in the case of level of mispricing, we acknowledge that this measure also has a limitation that even in the absence of arbitrage activity we may observe variation in mispricing due to changes in demand for the ETFs relative to that for the underlying securities. We compute $ETFSDMISPRC$ in two steps. First, for each ETF j, we calculate the standard deviation of the daily mispricing over calendar quarter q, which we label as $SDMISPRC_{j,q}$. Second, for each stock i in calendar quarter q, we compute the weighted average of $SDMISPRC_{j,q}$ across all J ETFs holding that stock, where the weight $w_{j,q-1}$ is the percent ownership of the ETF j in a given stock i at the end of the previous quarter $q-1$:

$$ETFSDMISPRC_{i,q} = \sum_{j=1}^{J} w_{j,q-1} \times SDMISPRC_{j,q} \tag{9}$$

Next, we use the level and standard deviation of the creation and redemption activities in an ETF as two of our additional proxies of arbitrage activity ($ETFABSCR$ and $ETFSDCR$). As mentioned earlier, APs hold the exclusive right to create and redeem ETF shares and they can conduct these market operations for two potential reasons. First, they use the creation and redemption processes to maintain the ETF price in line with the price of the underlying basket through the arbitrage mechanism. Second, APs occasionally create (redeem) shares to meet increasing (decreasing) market demand of the ETFs. However, it is rare that APs grow or shrink the ETFs by catering to specific client needs. Instead, APs will use the arbitrage mechanism to increase or decrease the shares outstanding of ETFs. For instance, if a given ETF is popular, the price of that ETF will reflect the increased demand creating a mispricing between the prices of the ETF and the underlying basket. In turn, this mispricing is reduced through the arbitrage mechanism which results in the creation of more ETF shares.

Specifically, for both these proxies, we first compute the daily net share creation and redemption for each ETF, which we impute from the change in ETF shares outstanding obtained from CRSP and Compustat. For the first of the two proxies, $ETFABSCR$, we take the sum of the absolute value of the net share creation and redemption for each ETF over each quarter, and then calculate its ETF ownership-weighted average. We use the absolute value of the flows because net creation or net redemption of ETF units will induce trading in the underlying securities. As a fund is shrinking or growing, it will have to dispose of, or purchase, the underlying securities—in either case demanding liquidity to conduct these operations. Formally, for each stock i in calendar quarter q:

$$ETFABSCR_{i,q} = \sum_{j=1}^{J} \left[w_{j,q-1} \times \frac{1}{D} \sum_{d=1}^{D} \left| \frac{SHRSOUT_{j,d} - SHRSOUT_{j,d-1}}{SHRSOUT_{j,d-1}} \right| \right] \tag{10}$$

where $SHRSOUT_{j,d}$ is the number of shares outstanding of ETF j at the end of day d. J is the total number of ETFs present in the ownership of a given stock i, and D is the number of days in a given quarter q. Finally, $w_{j,q-1}$ is the percent ownership of the ETF j in a given stock i at the end of the previous quarter $q-1$.

For the second proxy, $ETFSDCR$, we estimate the standard deviation of the daily net share creation and redemption for each ETF over each quarter, and then calculate its ETF ownership-weighted average for each stock in a manner analogous to $ETFSDMISPRC$. As in the case of mispricing, the standard deviation of the creation and redemption activities by APs reflects the active engagement of APs in the arbitrage mechanism.

$ETFABSCR$ and $ETFSDCR$ complement the previous two proxies related to mispricing. Contrary to mispricing which we observe at the end of the day, the ETF creation and redemption activities are the outcome of APs conducting arbitrage throughout the day. Again, these two proxies have at least one limitation in that arbitrage activities conducted over the course of the day by APs may not necessarily require them to create or redeem at the end of the day, once opposite positions are netted out. Moreover, APs do not have to necessarily create or redeem ETF shares at the end of the day as they can carry forward their net short or long positions in ETFs. Both these scenarios should lead to an underestimation of the actual arbitrage activities conducted by APs.

Finally, we use the turnover and short interest in an ETF ($ETFTURN$ and $ETFSHORT$) as our final two proxies for arbitrage activity. We obtain turnover ($ETFTURN$) and short interest ($ETFSHORT$) for each ETF from Compustat. These proxies do not have an equivalent counterpart in open-end funds since they exploit the added dimensionality of ETFs trading contemporaneously with the underlying stocks. Even though ETF turnover and ETF short interest may not always be motivated by an intention to arbitrage, they can create arbitrage opportunities through the demand shocks from market participants. For example, a hedge fund might short an ETF on the S&P 500 to hedge market risk associated with its long positions. Such a demand can create arbitrage opportunities when there is sufficient deviation between the price of the ETF and that of the underlying securities.

Table 8 reports the correlations between the six proxies of arbitrage activity. It is comforting to observe that all the correlations are positive. Moreover, the proxies are not perfectly correlated as the correlations range between 0.21 and 0.88, suggesting that they capture different dimensions of arbitrage activity.

To test whether greater arbitrage activity is associated with a stronger relation between ETF ownership and commonality in liquidity, we estimate our baseline specification (Equation 4) separately for stocks that are subject to different levels of arbitrage activity in the ETFs that own these stocks. Specifically, for each of the six proxies, we divide the stocks into two groups, the bottom quintile (lower arbitrage activity) and the balance (higher arbitrage activity). We form these groups within each decile of ETF ownership to control for the cross-sectional variation in the ETF ownership across stocks. Our results are qualitatively similar when we use other cutoffs such as quartiles, terciles, and medians, as well as using the interaction of two continuous variables: ETF ownership and each of the proxies of arbitrage activity.

The results in Table 9 consistently show that impact the ETF ownership on commonality in liquidity is higher for stocks that are subject to greater ETF arbitrage activity compared to the stocks with lower arbitrage activity. For instance, Model 1 reports the results for the $ETFAMISPRC$ proxy. We observe that the coefficient for $ETFOWN$ for stocks in the top four quintiles of the arbitrage activity proxy is 0.0639 which is significantly higher than the corresponding coefficient of 0.0459 for the stocks in the bottom quintile. The difference of 0.018 is significant at the 5% level ($F - statistic$ of 6.78). Remarkably, we observe similar coefficients for the two groups of stocks for each of the remaining five proxies of arbitrage activity, and the coefficient differences are highly significant at the 1% level in each model. Collectively, these findings suggest that the arbitrage mechanism designed to reduce pricing imbalances between ETFs and their underlying securities contributes to increase in the co-movement of liquidity among constituent stocks.

6. Establishing Causality of the Arbitrage Channel

Our results so far show that ETF ownership increases the commonality of liquidity of their underlying basket of securities and the arbitrage mechanism involving ETFs appears to be the source of this positive relation. To provide a causal interpretation of these findings, we use a natural experiment, which exploits a plausibly exogenous interruption in the arbitrage mechanism. Specifically, on August 24, 2015, trading was temporarily halted on 327 ETFs (about 20% of the US-listed ETFs) while many of the underlying stocks were still allowed to trade. According to Blackrock, several factors including "lack of price indications, widespread anomalous single stock pricing, uncertainty around hedging due to fear of 'broken trades,' delayed opens and trading halts in many stocks" impaired the ability of arbitrageurs to reduce ETF mispricing. Furthermore, Blackrock mentions that US-listed ETFs that invest in US equities were primarily affected by the trading halts. Since our study focuses only on these ETFs, the events of August 24, 2015 are particularly suited for our experiment.[13]

Events on this trading day allow us to directly test whether arbitrage trades that take advantage of the difference between the price of an ETF and the aggregated value of its constituents are indeed driving commonality in liquidity. When arbitrageurs are unable to establish arbitrage positions simultaneously in an ETF and its underlying constituent securities because of a trading halt in the ETF, trading across stocks referenced by the ETF will also not occur. Therefore, our experimental design helps us investigate whether liquidity commonality among the stocks referenced by the halted ETFs decreases and then subsequently increases when trading in the ETF is resumed.

Using high-frequency data from TAQ, we calculate for every stock i and second s an intra-day analog to the Amihud (2002) illiquidity measure, $illiq_{i,s}$.[14] Specifically, using every trade t reported to the consolidated tape on August 24, we calculate

$$illiq_{i,s} = \log \left[1 + \sum_{t \in s} \omega_{i,t} A_{i,t} \right] \tag{11}$$

[13]See US Equity Market Structure: Lessons from August 24. October 2015, Blackrock report. `https://www.blackrock.com/corporate/literature/whitepaper/viewpoint-us-equity-market-structure-october-2015.pdf`

[14]We drop all trades sold and reported out of sequence from the daily consolidated trades tape.

where $\omega_{i,t}$ is the relative dollar trade size, $S_{i,t}$, of trade t and $A_{i,t}$ is equal to

$$A_{i,t} = \frac{\left|\frac{P_{i,t}-P_{i,t-1}}{P_{i,t-1}}\right|}{S_{i,t}} \times 10^6$$

winsorized at the 99th percentile. We then estimate the following model in a pooled regression:

$$\Delta illiq_{i,s} = \alpha_i + \beta_{1,i} H_{i,s} \cdot ETFOWN_i \cdot \Delta illiq_{HighETF,s} + \beta_{2,i} ETFOWN_i \cdot \Delta illiq_{HighETF,s} + \beta_{3,i} H_{i,s} \cdot \Delta illiq_{HighETF,s} + \beta_{4,i} H_{i,s} \cdot$$

where $H_{i,s}$ is the ETF ownership weighted average of indicator variables reflecting a trading halt during second s in an ETF holding stock i. The resulting variable is continuously defined between zero and one. $\Delta illiq_{i,s}$ and $\Delta illiq_{HighETF,s}$ measure the change in the high-frequency illiquidity for a given stock (i) and stocks that have high ETF ownership ($HighETF$), respectively. Note that in estimating the high-frequency Amihud measure we add one before taking its logarithm to avoid excluding zero-return observations.

$ETFOWN_i$ is the ETF ownership in stock i computed for each stock on August 24, 2015 following Equation 1. $FE_{i,s}$ are stock and time (measured in seconds) fixed effects. Since we include stock and time fixed effects, we exclude the solitary terms $ETFOWN_i$ and $\Delta illiq_{HighETF,s}$ on the right-hand side of Equation 12. Standard errors are two-way clustered at the stock and time level. Note that the time fixed effects allows us to absorb supply-side effects on the commonality in liquidity to the extent that systematic tightness in funding liquidity affects all market makers simultaneously.

If commonality in liquidity is driven by the arbitrage mechanism in ETFs, trading halts in ETFs should impede this mechanism. This in turn should reduce the effect of ETF ownership on the commonality in liquidity of the stocks held by ETFs affected by these trading halts. Therefore, we would expect $\beta_{1,i}$ to be negative. We present the results from estimating Equation 12 in Model 1 of Table 10. To begin with, a positive and significant value of 13.0186 for $\beta_{2,i}$ corroborates our earlier finding of commonality in liquidity increasing in ETF ownership. More importantly, the coefficient $\beta_{1,i}$ in Model 1 is -21.7935 and highly significant. This implies that the effect of ownership on the commonality of liquidity is attenuated for stocks held by ETFs that were affected by trading halts on August 24th. This finding helps provide a causal interpretation supporting our hypothesis that ETF arbitrage is the underlying channel behind the relation between ETF ownership and commonality in stock liquidity.[15]

During the course of the day on August 24th, short-sale restrictions (SSRs) were invoked on 2,069 stocks on either the NYSE or the NASDAQ. Under Rule 201 (alternative uptick rule) of Regulation SHO, SSRs are

[15] Our results are robust to including the change in the market illiquidity, $\Delta illiq_{m,s}$, and its interactions with $ETFOWN$, $\Delta illiq_{HighETF,s}$, $H_{i,s}$ in Equation 12.

triggered when a stock price drops 10% below the previous day's closing price. When SSRs are triggered, short sale orders generally cannot be executed for the rest of the trading day at prices that are equal to or lower than the national best bid. The restrictions then carryover to the next trading day. In addition, to the SSRs there were 1,278 trading halts on August 24, of which 1,058 halts were in 327 ETFs (many halts were repeats in the same ETF), and 220 halts in 144 stocks. Note that many of the stocks that experienced trading halts that day were penny stocks and therefore are automatically excluded from our baseline Model 1 as we apply a $2 filter for selecting the stocks. We repeat our analysis after excluding the stocks that experienced SSRs and trading halts. The results in Model 2 continue to show a negative and significant coefficient $\beta_{1,i}$, confirming the robustness of our baseline results.

To further establish that the trading halts on August 24th are indeed affecting the commonality in liquidity and are not spurious, we conduct two falsification tests. First, we use a pseudo-event date of August 17, 2015 a week prior to the actual event date. Note that we intentionally select the same weekday (Monday) to allow for potential seasonality in the trading behavior during the week. For this test we assume that the same ETFs that suffered from trading halts on August 24th at different times of the day were also not trading (fictionally) at exactly those times on August 17th. In Model 3, the coefficient $\beta_{1,i}$ is not significant on August 17th, indicating that our prior findings for August 24th are not spurious. Second, we use the actual date of August 24, 2015 but randomize (i) which ETFs in our sample are affected by the trading halts and (ii) when the selected ETFs experience a trading halt through the entire day. Through these two randomizations, we effectively create placebo cases of ETFs that did not experience trading halts and pseudo times when there were no halts. However, we ensure that the draws of ETFs and halt durations match their actual averages on August 24th. The design of this second falsification test should alleviate the concerns that another pseudo-event date might not match the characteristics, such as high volatility, of August 24th, 2015. We conduct this test by reestimating Model 1 with 1,000 simulations using the high dimensional intraday data of ETF-stock-second level observations. Model 4, reports the average coefficients across the 1,000 simulations of Model 1. Again in this second falsification test, the coefficient $\beta_{1,i}$ is not significant, further validating the causal effect of ETF ownership on commonality in liquidity.

Overall, in this section we show that in periods where the arbitrage mechanism involving ETFs is interrupted, we observe a significant weakening of the relation between ETF ownership and commonality in liquidity. This in turn lends a causal interpretation to the arbitrage channel being the driver of this relation. Moreover, the two falsification tests help rule out the possibility that our findings are due to chance. Nonetheless, we caution against overemphasizing our findings and acknowledge that it is always challenging to isolate an effect using an extreme event when there can be several confounding factors at play.

7. Conclusion

There is little doubt that ETFs have provided vast benefits to institutional and retail investors alike. The spectacular growth in ETFs over the last decade is a testimony to their merits as an important financial innovation. ETFs improve welfare by providing investors an inexpensive avenue to diversify their holdings and intraday liquidity, among other benefits. Nonetheless, the rapid growth of ETFs necessitates a better understanding of the consequences of having an additional layer of ETF trading activity on top of the trading that already exists in the underlying securities. In that respect, a growing academic literature has made inroads in furthering our understanding of these consequences.

This paper contributes to this literature by documenting that ETF ownership exacerbates the comovement in the liquidity of constituent stocks. Moreover, we show that the underlying arbitrage mechanism that ensures little deviation between the prices of the ETFs and the underlying securities, drives the commonality in liquidity of the securities included in the ETF portfolios. This result holds for different stock market capitalizations and different market conditions. A falsification test using a randomly assigned set of stocks to construct the commonality in liquidity measure does not yield the same results. Moreover, the effect of ETF ownership on liquidity commonality is independent from that of the ownership by index mutual funds, active mutual funds, and other institutional investors. We also use a methodology similar to Antón and Polk (2014) to conduct analysis at the stock-pair level by identifying the common ownership of ETFs in each stock pair, both in terms of the percentage ownership as well as the number of ETFs that hold the stock pair. Our findings from this complementary analysis continues to support our hypothesis that ETF ownership influences the commonality in stock liquidity. Furthermore, we establish a causal relation between ETF ownership and liquidity commonality through a quasi-natural experiment that uses the reconstitution of Russell 1000 and Russell 2000 indexes to capture a source of exogenous variation in common ETF ownership. Consistent with a causal interpretation, we find that two stocks exhibit increased correlation in liquidity subsequent to an increase in the ETF ownership which those stocks have in common. We supplement that experiment by employing an instrumental variable approach to differentiate between the changes in aggregate ETF ownership in stocks and the common ownership of ETFs holding the same stock pair.

Next, we shed light on the channels for changes in the liquidity commonality by showing that greater arbitrage activities both in the primary and secondary markets of ETFs are associated with an increase in the commonality of stock liquidity. Further, we use another quasi-natural experiment that exploits the recent events of August 24, 2015 when trading was halted in certain ETFs to demonstrate that such halts are associated with a decline in the commonality of the liquidity due to an interruption in the arbitrage mechanism. We use two falsification tests using a pseudo-event date as well as random ETFs halt on the actual event date. Contrary to the actual trading halts where we observe a decline in commonality in liquidity, none of these two tests reveal a significant change in commonality. Collectively, these tests underscore the arbitrage mechanism as the main channel driving the relation between ETF ownership and commonality in liquidity of underlying securities. In the process, these findings also highlight the important differences between the mechanisms associated with the liquidity demands of ETFs versus actively managed open-end mutual funds. Unlike in case of ETFs, the demand from open-end funds does not entail an intraday arbitrage mechanism and is subject to significant discretion of the fund managers on account of their private information.

Overall, our paper contributes to the policy debate of widespread implications of ETFs in security markets. We show that higher ETF ownership of stocks can reduce the ability of investors to diversify liquidity risk due to an increase in the commonality in liquidity of stocks included in ETF portfolios.

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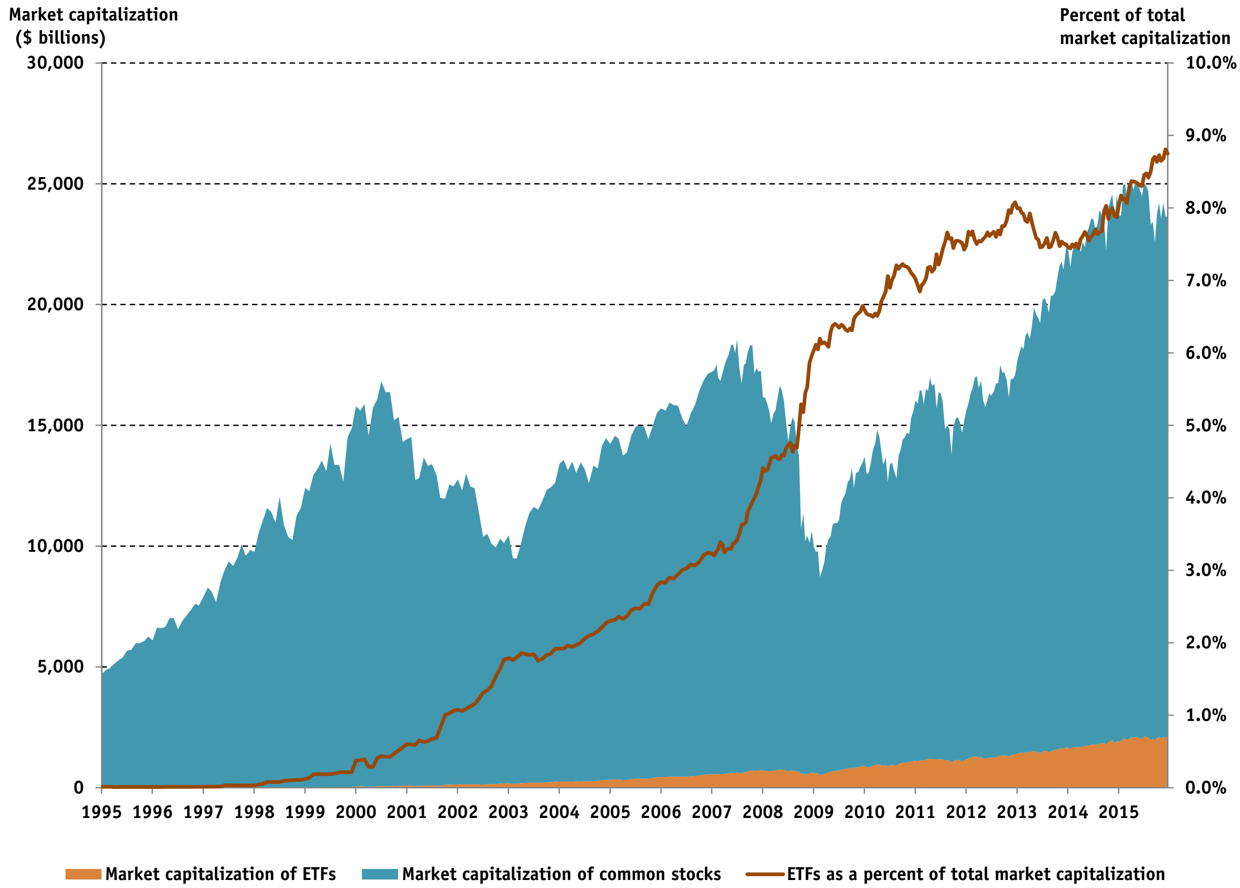

Figure 1. Assets Under Management (AUM) of ETFs trading on US stock exchanges relative to the total market capitalization of the US equity market. Market capitalization information is obtained from CRSP on common shares (CRSP share code 10 and 11) and Exchange Traded Funds, which were identified using CRSP and Compustat. The bottom area uses the left scale and represents the growth in ETFs. ETFs as of December 31, 2015 have a market capitalization of about 2 trillion dollars. The top area uses the left scale and represents the market capitalization of all CRSP common shares. The line uses the right scale and represents the percentage of ETF market capitalization to the total market capitalization (common shares and ETFs). The line illustrates the steady and dramatic growth of ETF products, which as of December 31, 2015 had an AUM representing 8.75% of the US equity markets.

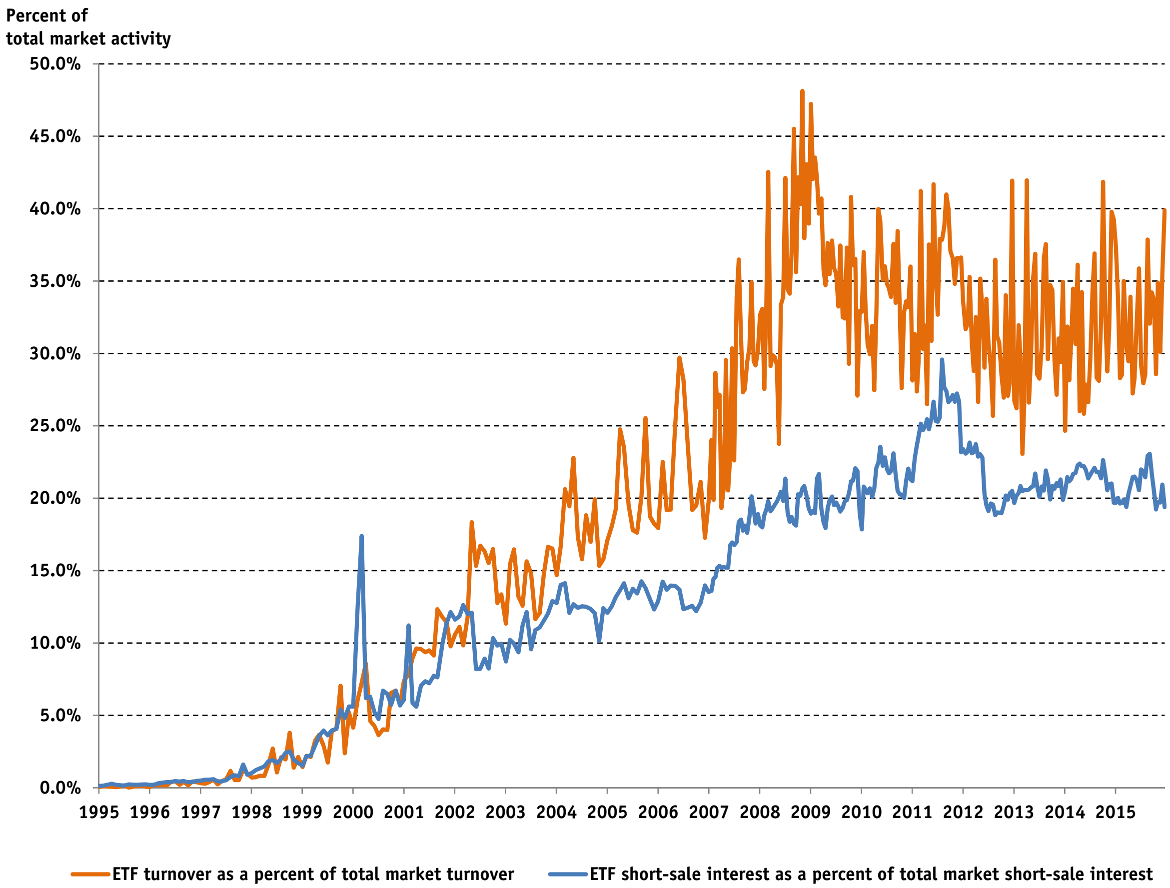

Figure 2. ETF turnover and short-sale interest as a percentage of total common share and ETF market turnover and short-sale interest (January 1995-December 2015) Trading volume information is obtained from CRSP on common shares (CRSP share code 10 and 11) and Exchange Traded Funds, which were identified using CRSP and Compustat. Short-sale interest was obtained from Compustat. The percentage of ETF trading volume as a percentage of total common share and ETF trading volume has increased from less than 5% from 1995 to 2000 to between 25% to 45% in the period 2008 to 2015. Similarly, ETFs represent a growing proportion of all equity sold short. Over the period 2008 to 2015, the short-sale interest on all ETFs has steadily represented about 20% of all equity short-sale interest.

Table 1
Descriptive Statistics

$\beta_{HighETF}$ measures the commonality in liquidity with respect to the illiquidity of stocks that are in the top quartile of ETF ownership as in Koch et al. (2016). $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ are the percent ownership in a stock held by ETFs, index open-end mutual funds, active open-end mutual funds, and all other institutional investors, respectively. $SIZE$ is the stock's market capitalization in \$ millions and $AMIHUD$ is the Amihud (2002) illiquidity level. β_{mxs} is the stock's beta calculated using the weighted-average returns excluding the given stock on all CRSP stocks as the proxy for market returns. $ETFAMISPRC$ measures the ETF ownership weighted average arbitrage opportunities of ETFs that hold a given stock, and is calculated as the sum of the absolute value of the daily difference between the ETF NAV and the ETF end-of-the-day price aggregated over each quarter. $ETFSDMISPRC$ is the standard deviation of the daily mispricing over the quarter. $ETFABSFLOWS$ represents for a given stock the absolute value of daily ETF net flows (creation-redemptions) summed over the quarter for the ETFs that hold the stock. $ETFSDFLOWS$ is the standard deviation of the daily ETF net flows for the ETFs that hold the stock. $ETFTURN$ and $ETFSHORT$ are the ETF ownership-weighted average ETF turnover and ETF short-sale interest for a given stock, respectively. $\rho_{\Delta liquidity}$ is the pairwise correlation in changes in the Amihud (2002) liquidity between any two different stocks calculated over the quarter. $\rho_{returns}$ is the pairwise correlation in returns between any two different stocks calculated over the quarter. $ETFFCAP$, $INXFCAP$, and $MFFCAP$, measure the degree to which two stocks have connected ownership through ETFs, index mutual funds, and active mutual funds, respectively. Connected ownership is calculated using the methodology in Antón and Polk (2014). $ETFNUM$, $INXNUM$, and $MFNUM$ measure the number of funds any two stocks have in common for ETFs, index mutual funds, and active mutual funds, respectively.

Variable	N	Mean	Std. Dev	25^{th} Pct.	Median	75^{th} Pct
Commonality in Liquidity Measure						
$\beta_{HighETF}$	294,613	0.19	1.87	-0.83	0.27	1.34
Institutional Ownership Variables						
$ETFOWN$	310,179	2.63%	2.94%	0.25%	1.53%	4.12%
$INXOWN$	296,710	2.30%	1.79%	0.81%	2.12%	3.32%
$MFOWN$	288,026	14.20%	11.83%	2.98%	12.48%	23.18%
$OTHROWN$	293,380	29.38%	18.68%	12.94%	29.63%	43.84%
Control Variables						
$SIZE$	313,312	\$3,412.7	\$16,666.3	\$68.6	\$299.6	\$1,361.0
$AMIHUD$	306,746	0.17	0.26	0.00	0.02	0.27
β_{mxs}	306,018	0.90	0.73	0.39	0.88	1.35
Arbitrage Channels						
$ETFAMISPRC$	248,039	0.08%	0.10%	0.01%	0.04%	0.09%
$ETFSDMISPRC$	248,055	0.06%	0.07%	0.01%	0.04%	0.09%
$ETFABSFLOWS$	248,039	0.46%	0.53%	0.07%	0.31%	0.63%
$ETFSDFLOWS$	248,039	1.12%	2.45%	0.20%	0.72%	1.32%
$ETFTURN$	248,039	4.51%	6.19%	0.20%	2.28%	6.70%
$ETFSHORT$	248,039	13.23%	15.40%	0.47%	7.72%	21.06%
Pairwise Correlation Variables						
$\rho_{\Delta liquidity}$	550,300,404	3.38%	18.02%	-8.60%	3.45%	15.48%
$\rho_{returns}$	550,300,404	15.96%	20.82%	1.94%	15.34%	29.45%
$ETFFCAP$	550,300,404	1.25%	1.71%	0.08%	0.65%	1.71%
$INXFCAP$	550,300,404	0.44%	0.74%	0.03%	0.19%	0.55%
$MFFCAP$	550,300,404	1.48%	2.13%	0.13%	0.79%	1.93%
$ETFNUM$	550,300,404	5.96	10.05	1.00	2.00	7.00
$INXNUM$	550,300,404	16.57	28.08	2.00	7.00	22.00
$MFNUM$	550,300,404	16.63	39.65	2.00	7.00	19.00

Table 2
ETF Ownership and Commonality in Liquidity

This table presents baseline results of regressions of commonality in liquidity $\beta_{HighETF}$ on lagged ownership. Panel A, reports results on the effect of $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ on commonality in liquidity $\beta_{HighETF}$. $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ are the percent ownership in a stock held by ETFs, index open-end mutual funds, active open-end mutual funds, and all other institutional investors, respectively. $\beta_{HighETF}$ measures the commonality in liquidity with respect to the illiquidity of stocks that are in the top quartile of ETF ownership as in Koch et al. (2016). Controls for the stock's market capitalization ($SIZE$) and Amihud (2002) illiquidity levels are included. In Models 1 through 3, we include each category of institutional investor separately and in Model 4 we examine include all of them together. Quarter and stock fixed-effects are included in all specifications and standard errors are double clustered by quarter and stock. Panel B, reports results with additional controls, and using only time fixed-effects. Model 1, adds β_{mxs} the stock's beta calculated using the weighted-average returns excluding the given stock on all CRSP stocks as the proxy for market returns and adds $\beta_{m,t-1}$ which is the lagged beta on the aggregate market illiquidity. Model 2 appends Model 1 with $\beta_{HighETF,t-1}$ that is the lagged value of the commonality in liquidity measure. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Baseline Regressions

	(1)	(2)	(3)	(4)
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	0.0660***			0.0584***
	(9.93)			(8.89)
$INXOWN_{t-1}$		0.0370***		0.0128**
		(7.13)		(2.53)
$MFOWN_{t-1}$			0.0316***	0.0186***
			(5.93)	(3.73)
$OTHROWN_{t-1}$				-0.0028
				(-0.50)
$SIZE_{t-1}$	0.0239**	0.0329***	0.0196*	0.0203*
	(2.47)	(3.40)	(1.86)	(1.94)
$AMIHUD_{t-1}$	-0.0463	-0.0579*	-0.0869***	-0.0594*
	(-1.65)	(-1.98)	(-2.734)	(-1.92)
N	275,314	267,959	261,358	251,356
R^2	0.055	0.054	0.055	0.056
Period	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock

Panel B: Baseline Regressions with Additional Controls

	(1)	(2)	(3)	(4)
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	0.0584***	0.0547***	0.0549***	0.0542***
	(8.89)	(8.42)	(8.62)	(8.31)
$INXOWN_{t-1}$	0.0128**	0.0131**	0.0132**	0.0125**
	(2.53)	(2.54)	(2.53)	(2.37)
$MFOWN_{t-1}$	0.0186***	0.0188***	0.0184***	0.0188***
	(3.73)	(3.63)	(3.54)	(3.53)
$OTHROWN_{t-1}$	-0.0028	-0.0037	-0.0042	-0.0036
	(-0.50)	(-0.65)	(-0.73)	(-0.63)
$SIZE_{t-1}$	0.0203*	0.0226**	0.0229**	0.0226**
	(1.94)	(2.33)	(2.36)	(2.31)
$AMIHUD_{t-1}$	-0.0594*	-0.0555*	-0.0569*	-0.0596*
	(-1.92)	(-1.76)	(-1.80)	(-1.93)
$\beta_{mxs,t-1}$		0.0151**	0.0157**	0.0154**
		(2.26)	(2.32)	(2.31)
$\beta_{m,t-1}$		0.0192***	0.0151**	0.0157**
		(7.00)	(2.19)	(2.28)
$\beta_{HighETF,t-1}$			-0.0050	-0.0030
			(-0.68)	(-0.41)
$\beta_{HighMF,t-1}$				-0.0012
				(-0.42)
N	251,356	242,536	241,979	238,775
R^2	0.056	0.059	0.059	0.059
Period	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock

Table 3
ETF ownership and Commonality in Liquidity by Index Membership

This table reports results on the effect of $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ on commonality in liquidity $\beta_{HighETF}$ for stocks that are members of the Russell 3000 (Model 2), Russell 2000 (Model 3) and S&P 500 (Model 4). $\beta_{HighETF}$ measures the commonality in liquidity with respect to the illiquidity of stocks that are in the top quartile of ETF ownership as in Koch et al. (2016). Model 1, reports the baseline results of Model 4 in Table 2, Panel A. $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ are the percent ownership in a stock held by ETFs, index open-end mutual funds, active open-end mutual funds, and all other institutional investors, respectively. Controls for the stock's market capitalization ($SIZE$) and Amihud (2002) illiquidity levels ($AMIHUD$) are included. The index membership weight, $RUSSELL3000.WEIGHT$, $RUSSELL2000.WEIGHT$, $SP500.WEIGHT$ for each stock are included as an additional control in Model 2, 3, and 4, respectively. Quarter and stock fixed-effects are included in all specifications and standard errors are double clustered by quarter and stock. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	0.0584***	0.0424***	0.0322***	0.0674***
	(8.89)	(6.05)	(3.95)	(3.87)
$INXOWN_{t-1}$	0.0128**	0.0108*	-0.0010	-0.0158
	(2.53)	(1.82)	(-0.18)	(-0.61)
$MFOWN_{t-1}$	0.0186***	0.0196***	0.0057	0.0062
	(3.73)	(3.36)	(0.87)	(0.38)
$OTHROWN_{t-1}$	-0.0028	0.0017	-0.0063	-0.0042
	(-0.50)	(0.26)	(-0.82)	(-0.23)
$SIZE_{t-1}$	0.0203*	0.0026	0.0543***	-0.0230
	(1.94)	(0.26)	(4.33)	(-0.91)
$AMIHUD_{t-1}$	-0.0594*	-0.0709	0.1510**	3.9900
	(-1.92)	(-1.09)	(2.07)	(0.45)
$RUSELL3000.WEIGHT_{t-1}$		-18.8900		
		(-1.61)		
$RUSELL2000.WEIGHT_{t-1}$			-13.5200	
			(-0.60)	
$SP500.WEIGHT_{t-1}$				-6.7360
				(-0.70)
N	251,356	165,325	110,860	27,494
R^2	0.056	0.059	0.071	0.061
Period	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Universe	All Stocks	Russell 3000	Russell 2000	S&P500

Table 4
ETF Ownership and Commonality in Liquidity Excluding the Crisis Period

This table reports results on the effect of $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ on commonality in liquidity $\beta_{HighETF}$ for different time periods. $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ are the percent ownership in a stock held by ETFs, index open-end mutual funds, active open-end mutual funds, and all other institutional investors, respectively. $\beta_{HighETF}$ measures the commonality in liquidity with respect to the illiquidity of stocks that are in the top quartile of ETF ownership as in Koch et al. (2016). Controls for the stock's market capitalization ($SIZE$) and Amihud (2002) illiquidity levels are included. Quarter and stock fixed-effects are included in all specifications and standard errors are double clustered by quarter and stock. Model 1 recalls the baseline results from Table 2, Model 4. Model 2 excludes the crisis period 2007-2009 from the sample. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	0.0584***	0.0566***
	(8.89)	(7.76)
$INXOWN_{t-1}$	0.0128**	0.0180***
	(2.53)	(3.37)
$MFOWN_{t-1}$	0.0186***	0.0215***
	(3.73)	(3.93)
$OTHROWN_{t-1}$	-0.0028	-0.0037
	(-0.50)	(-0.66)
$SIZE_{t-1}$	0.0203*	0.0173
	(1.94)	(1.48)
$AMIHUD_{t-1}$	-0.0594*	-0.0357
	(-1.92)	(-1.03)
N	251,356	221,940
R^2	0.056	0.060
Period	2000-2016	excl. 2007-2009
Fixed Effects	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock

Table 5
Pairwise Correlation in Liquidity of Stocks with Common ETF ownership

Panel A, reports results on the effect of the ETF, passive, and active mutual fund common ownership between two different stocks i and j ($ETFFCAP$, $INXFCAP$, $MFFCAP$, respectively) on the pairwise correlation of changes in Amihud (2002) liquidity ($\rho_{\Delta liquidity}$).
Panel B, reports results on the effect of the number of ETF, index, and active mutual funds that connect two different stocks i and j ($ETFNUM$, $INXNUM$, and $MFNUM$, respectively) on the pairwise correlation of changes in Amihud (2002) liquidity ($\rho_{\Delta liquidity}$). For Panel A and B, all specifications include quarter interacted with stock i and quarter interacted with stock j fixed effects. Additionally, Model 5 of each panel includes the correlation in returns of the two stocks ($\rho_{returns}$) estimated over the previous quarter. Standard errors are triple-clustered by quarter, stock i, and stock j. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: FCAP Measure

	(1)	(2)	(3)	(4)	(5)
	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$
$ETFFCAP_{t-1}$	0.0126***			0.0071***	0.0064***
	(10.12)			(8.65)	(8.42)
$INXFCAP_{t-1}$		0.0087***		0.0023*	0.0021*
		(5.24)		(1.91)	(1.90)
$MFFCAP_{t-1}$			0.0081***	0.0053***	0.0048***
			(14.19)	(15.32)	(15.41)
$\rho_{returns,t-1}$					0.0397***
					(10.67)
N	550,299,832	550,299,832	550,299,832	550,299,832	550,299,832
R^2	0.103	0.103	0.103	0.103	0.104
Period	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Qtr.× Stock i, and Qtr.× Stock j	Qtr.× Stock i, and Qtr.× Stock j	Qtr.× Stock i, and Qtr.× Stock j	Qtr.× Stock i, and Qtr.× Stock j	Qtr.× Stock i, and Qtr.× Stock j
Clustering	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j

Panel B: No. of ETFs Holding Both Stocks

	(1)	(2)	(3)	(4)	(5)
	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$
$log(1+ETFNUM)_{t-1}$	0.0241***			0.0185***	0.0174***
	(17.39)			(12.21)	(12.09)
$log(1+INXNUM)_{t-1}$		0.0168***		0.0007	0.0003
		(16.03)		(1.16)	(0.60)
$log(1+MFNUM)_{t-1}$			0.0141***	0.0049***	0.0046***
			(13.82)	(8.82)	(8.64)
$\rho_{returns,t-1}$					0.0314***
					(11.27)
N	550,299,832	550,299,832	550,299,832	550,299,832	550,299,832
R^2	0.105	0.105	0.104	0.106	0.106
Period	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Qtr.× Stock i, and Qtr.× Stock j	Qtr.× Stock i, and Qtr.× Stock j	Qtr.× Stock i, and Qtr.× Stock j	Qtr.× Stock i, and Qtr.× Stock j	Qtr.× Stock i, and Qtr.× Stock j
Clustering	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j

Table 6
Evidence from Exogenous Variation in Common ETF Ownership Consequent to Reconstitution of Russell Indexes

This table reports estimates from a design exploiting the exogenous changes in ETF ownership around the cutoff between the Russell 1000 and Russell 2000 indexes and the annual reconstitution of the two indexes. We examine the effect on the commonality in changes in Amihud (2002) liquidity between any two different stocks ($\rho_{\Delta liquidity}$) on the degree to which those two stocks are connected through common ETF ownership $ETFFCAP$ and the interaction of $ETFFCAP$ with an indicator variable, $SWITCH$, determining the reassignment of one of the stocks in the Russell indexes. The $SWITCH$ variable varies according to the specification. $SWITCH_A$ takes the value of 1 if both stocks switched from the Russell 1000 to 2000, and 0 otherwise. $SWITCH_B$ takes the value of 1 if one of the stocks switched into the Russell 2000 and the other remained in the Russell 2000, and 0 otherwise. $SWITCH_C$ takes the value of 1 if both stocks switched from the Russell 2000 to the Russell 1000, and 0 otherwise. $SWITCH_D$ takes the value of 1 if one of the stocks switched into the Russell 1000 and the other remained in the Russell 2000, and 0 otherwise. We also control for connectedness of the two stocks through their index and active mutual fund common ownership, $INXFCAP$, and $MFFCAP$, respectively, and the interaction of those measures with the $SWITCH$ variable. Panel A, uses a sample of 100 stocks on either side of the market capitalization cutoff between the Russell 1000 and Russell 2000 indexes (the 100 lowest stocks, and 100 highest stocks by market capitalization, in the Russell 1000 and 2000 indexes, respectively). Panel B increases the sample to 200 stocks on either side of the same cutoff. For both panels A and B, we include quarter fixed effects and stock fixed effects for each stock in the pair, and the correlation in the returns of the two stocks ($\rho_{returns}$) estimated over the previous quarter. Standard errors are triple-clustered by quarter, stock i, and stock j. t-statistics are triple-clustered at the quarter, stock i, and stock j level, and are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: 100 stock cutoff

	Switch from Russell 1000 to 2000		Switch from Russell 2000 to 1000	
$SWITCH$	$SWITCH_A$	$SWITCH_B$	$SWITCH_C$	$SWITCH_D$
	(1)	(2)	(3)	(4)
	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$
$ETFFCAP_{t-1}$	0.0056***	0.0033*	0.0071***	0.0058***
	(3.70)	(2.00)	(4.98)	(3.63)
$ETFFCAP_{t-1} \times SWITCH$	0.0027	0.0080***	-0.0080**	-0.0001
	(1.14)	(4.11)	(-2.36)	(-0.05)
$INXFCAP_{t-1}$	0.0009	0.0012*	0.0008	0.0014
	(1.24)	(1.74)	(0.96)	(1.53)
$INXFCAP_{t-1} \times SWITCH$	0.0000	-0.0010	0.0009	-0.0014
	(0.02)	(-0.77)	(0.58)	(-1.14)
$MFFCAP_{t-1}$	0.0058***	0.0064***	0.0039***	0.0061***
	(5.28)	(5.60)	(5.67)	(5.28)
$MFFCAP_{t-1} \times SWITCH$	-0.0014	-0.0042***	0.0062***	-0.0012
	(-0.69)	(-2.75)	(3.10)	(-1.34)
$\rho_{returns,t-1}$	0.0461***	0.0458***	0.0451***	0.0462***
	(7.85)	(7.84)	(7.95)	(7.90)
N	527,449	527,449	527,449	527,449
R^2	0.054	0.054	0.054	0.054
Period	2000-2007	2000-2007	2000-2007	2000-2007
Fixed Effect	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j
Clustering	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j

Continued from table 6

Panel B: 200 Stock Cutoff

	Switch from Russell 1000 to 2000		Switch from Russell 2000 to 1000	
$SWITCH$	$SWITCH_A$	$SWITCH_B$	$SWITCH_C$	$SWITCH_D$
	(1)	(2)	(3)	(4)
	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$	$\rho_{\Delta liquidity,t}$
$ETFFCAP_{t-1}$	0.0074***	0.00551***	0.0081***	0.0082***
	(5.97)	(4.65)	(6.55)	(6.40)
$ETFFCAP_{t-1} \times SWITCH$	0.0048**	0.0073***	-0.0072**	-0.0049**
	(2.74)	(4.45)	(-2.05)	(-2.66)
$INXFCAP_{t-1}$	0.0000	0.0004	0.0001	0.0001
	(0.07)	(0.63)	(0.14)	(0.12)
$INXFCAP_{t-1} \times SWITCH$	0.00174	-0.0000	-0.0002	0.0007
	(1.25)	(-0.05)	(-0.08)	(0.76)
$MFFCAP_{t-1}$	0.0050***	0.0053***	0.0044***	0.0048***
	(8.78)	(9.08)	(10.21)	(8.23)
$MFFCAP_{t-1} \times SWITCH$	-0.0013	-0.0019**	0.0052***	0.0006
	(-1.12)	(-2.11)	(2.76)	(0.99)
$\rho_{returns,t-1}$	0.0556***	0.0554***	0.0552***	0.0557***
	(13.69)	(13.75)	(13.61)	(13.73)
N	2,079,314	2,079,314	2,079,314	2,079,314
R^2	0.052	0.053	0.052	0.052
Period	2000-2007	2000-2007	2000-2007	2000-2007
Fixed Effect	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j
Clustering	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j	Qtr., Stock i, Stock j

Table 7
Russell Reconstitution Instrumental Variables Approach

This table reports the two-stage least squares (2SLS) estimates from a design exploiting the exogenous changes in ETF ownership around the cutoff between the Russell 1000 and Russell 2000 indexes. In the first stage, the $ETFFCAP$ measure of the common ETF ownership between any two given stocks is regressed on the log market capitalization of the first stock and of the second stock and a $SWITCH$ indicator variable. The $SWITCH$ variable varies according to the specification. $SWITCH_A$ takes the value of 1 if both stocks switched from the Russell 1000 to 2000, and 0 otherwise. $SWITCH_B$ takes the value of 1 if one of the stocks switched into the Russell 2000 and the other remained in the Russell 2000, and 0 otherwise. $SWITCH_C$ takes the value of 1 if both stocks switched from the Russell 2000 to the Russell 1000, and 0 otherwise. $SWITCH_D$ takes the value of 1 if one of the stocks switched into the Russell 1000 and the other remained in the Russell 2000, and 0 otherwise. In the second stage, the correlation in the changes in Amihud (2002) liquidity between the two stocks ($\rho_{\Delta liquidity,t}$) is regressed against the predicted value of $ETFFCAP$ ($\widehat{ETFFCAP}$) and the log market capitalization of the first and second stock. Panel A, uses a sample of 100 stocks on either side of the market capitalization cutoff between the Russell 1000 and Russell 2000 indexes (the 100 lowest stocks, and 100 highest stocks by market capitalization, in the Russell 1000 and 2000 indexes, respectively). Panel B increases the sample to 200 stocks on either side of the same cutoff. t-statistics are triple-clustered at the quarter, stock 1, and stock 2 level, and are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: 100 stock cutoff

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$ETFFCAP$	$\rho_{\Delta liquidity,t}$	$ETFFCAP$	$\rho_{\Delta liquidity,t}$	$ETFFCAP$	$\rho_{\Delta liquidity,t}$	$ETFFCAP$	$\rho_{\Delta liquidity,t}$
$log(1+MKTCAP_1)$	0.0585	0.0055	0.18157**	0.0056	-0.0689	-0.0014	-0.0641	0.0059
	(0.88)	(1.57)	(2.63)	(1.60)	(-1.03)	(-0.15)	(-1.01)	(1.68)
$log(1+MKTCAP_2)$	0.0499	0.0067***	0.12978**	0.0067***	-0.0044	0.0051	-0.0674	0.0068***
	(0.84)	(3.23)	(2.18)	(3.24)	(-0.07)	(1.05)	(-1.16)	(3.31)
$\widehat{ETFFCAP}$		0.0204***		0.0204***		-0.06024		0.0241***
		(5.00)		(6.57)		(-1.02)		(4.46)
$SWITCH_A$	0.6628***							
	(9.67)							
$SWITCH_B$			0.8814***					
			(11.99)					
$SWITCH_C$					-0.1016*			
					(-1.76)			
$SWITCH_D$							-0.3792***	
							(-9.70)	
N	531,361	527,449	531,361	527,449	531,361	527,449	531,361	527,449
R^2	0.675	0.041	0.709	0.041	0.658	-0.020	0.678	0.040
Period	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2
Clustering	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2

Continued from table 7

Panel B: 200 Stock Cutoff

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$ETFFCAP$	$\rho_{\Delta liquidity,t}$	$ETFFCAP$	$\rho_{\Delta liquidity,t}$	$ETFFCAP$	$\rho_{\Delta liquidity,t}$	$ETFFCAP$	$\rho_{\Delta liquidity,t}$
$log(1+MKTCAP_1)$	0.2178***	0.0002	0.3519***	0.0012	0.1668**	0.0043	0.1781**	0.0010
	(2.79)	(0.06)	(4.62)	(0.36)	(2.07)	(1.05)	(2.39)	(0.29)
$log(1+MKTCAP_2)$	0.1068	0.0030	0.2196***	0.0035	0.0784	0.0047*	0.0562	0.0034
	(1.64)	(1.49)	(3.43)	(1.64)	(1.17)	(1.86)	(0.89)	(1.59)
$ET\widehat{FFC}AP$		0.0242***		0.0171***		-0.0047		0.0186***
		(6.05)		(4.72)		(-0.35)		(7.03)
$SWITCH_A$	0.5472***							
	(8.67)							
$SWITCH_B$			0.6841***					
			(10.32)					
$SWITCH_C$					-0.26829***			
					(-4.87)			
$SWITCH_D$							-0.4701***	
							(-10.59)	
N	2,094,530	2,079,314	2,094,530	2,079,314	2,094,530	2,079,314	2,094,530	2,079,314
R^2	0.602	0.036	0.633	0.038	0.594	0.034	0.620	0.037
Period	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2	Stock1, Stock2
Clustering	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2	Qtr., Stock1, Stock2

Table 8

Correlations Between the Different Proxies of Arbitrage Activity

$ETFAMISPRC$ measures the ETF ownership-weighted average of the sum of the absolute value of the daily difference between the ETF NAV and the ETF end-of-the-day price aggregated over each quarter. $ETFSDMISPRC$ is the standard deviation of that daily difference over the quarter. $ETFABSCR$ represents for a given stock the absolute value of daily ETF creation minus redemptions summed over the quarter for the ETFs that hold the stock. For a given stock, $ETFSDCR$ is the standard deviation over the quarter of the daily net creation or redemption of ETFs that own the stock. $ETFTURN$ and $ETFSHORT$ are the ETF ownership-weighted average ETF turnover and ETF short-sale interest for a given stock over the quarter, respectively.

	$ETFABSMISPRC$	$ETFSDMISPRC$	$ETFABSCR$	$ETFSDCR$	$ETFTURN$	$ETFSHORT$
$ETFABSMISPRC$	1.00					
$ETFSDMISPRC$	0.76	1.00				
$ETFABSCR$	0.37	0.53	1.00			
$ETFSDCR$	0.21	0.29	0.56	1.00		
$ETFTURN$	0.30	0.43	0.75	0.23	1.00	
$ETFSHORT$	0.29	0.43	0.79	0.28	0.88	1.00

Table 9
ETF Ownership and Commonality in Liquidity: Evidence of Arbitrage Channel

This table reports results on the effect of ETF ownership $ETFOWN$ on commonality in liquidity for two groups of stocks classified by the magnitude of ETF arbitrage activity in them. For each of the six proxies of arbitrage activity, the stocks are split into two groups, the bottom quintile (low arbitrage) and the balance (high arbitrage). These groups are formed within each decile of ETF ownership to control for the cross-sectional variation in the ETF ownership across stocks. Models 1 through 6 report the results for the six proxies that include $ETFAMISPRC$, $ETFSDMISPRC$, $ETFABSCR$, $ETFSDCR$, $ETFTURN$ and $ETFSHORT$. Each of the models simulataneously controls for the ownership of other institutional investors including open-ended index funds ($INXOWN$), active open-end funds ($MFOWN$), and all other institutional investors ($OTHROWN$). $\beta_{HighETF}$ measures the commonality in liquidity with respect to the illiquidity of stocks that are in the top quartile of ETF ownership as in Koch et al. (2016). Controls for the stock's market capitalization ($SIZE$) and Amihud (2002) illiquidity levels ($AMIHUD$) are included. $ETFAMISPRC$ measures the ETF ownership-weighted average of the sum of the absolute value of the daily difference between the ETF NAV and the ETF end-of-the-day price aggregated over each quarter. $ETFSDMISPRC$ is the standard deviation of that daily difference over the quarter. $ETFABSCR$ represents for a given stock the absolute value of daily ETF creation minus redemptions summed over the quarter for the ETFs that hold the stock. For a given stock, $ETFSDCR$ is the standard deviation over the quarter of the daily net creation or redemption of ETFs that own the stock. $ETFTURN$ and $ETFSHORT$ are the ETF ownership-weighted average ETF turnover and ETF short-sale interest for a given stock over the quarter, respectively. Quarter and stock fixed-effects are included in all specifications and standard errors are double clustered by quarter and stock. t-statistics for the coefficients are reported in parentheses with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively. F-statistics for the differences in the estimated coefficients on the ETF ownership of stocks subject to low arbitrage activity ($ETFOWN_{LowArbitrage}$) and high arbitrage activity ($ETFOWN_{HighArbitrage}$) are also reported.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\beta_{HighETF,t}$	$\beta_{HighETF}$	$\beta_{HighETF}$	$\beta_{HighETF}$	$\beta_{HighETF}$	$\beta_{HighETF}$
$ETFOWN_{t-1,LowArbitrage}$	0.0459***	0.0374***	0.0478***	0.0454***	0.0400***	0.0455***
	(6.48)	(5.49)	(7.01)	(6.81)	(6.00)	(6.73)
$ETFOWN_{t-1,HighArbitrage}$	0.0639***	0.0679***	0.0660***	0.0636***	0.0659***	0.0657***
	(8.30)	(8.74)	(8.62)	(8.28)	(8.44)	(8.37)
$INXOWN_{t-1}$	0.0129**	0.0122**	0.0126**	0.0127**	0.0129**	0.0129**
	(2.54)	(2.39)	(2.45)	(2.56)	(2.57)	(2.52)
$MFOWN_{t-1}$	0.0187***	0.0189***	0.0188***	0.0188***	0.0188***	0.0189***
	(3.75)	(3.80)	(3.675)	(3.79)	(3.73)	(3.73)
$OTHROWN_{t-1}$	-0.0023	-0.0024	-0.0023	-0.0028	-0.0031	-0.0024
	(-0.41)	(-0.42)	(-0.42)	(-0.50)	(-0.55)	(-0.44)
$SIZE_{t-1}$	0.0189*	0.0183*	0.0188*	0.0200*	0.0198*	0.0191*
	(1.77)	(1.71)	(1.78)	(1.88)	(1.86)	(1.81)
$AMIHUD_{t-1}$	-0.0638**	-0.0666**	-0.0640**	-0.0608*	-0.0631**	-0.0639**
	(-2.06)	(-2.14)	(-2.07)	(-1.94)	(-2.02)	(-2.07)
N	248,587	248,581	248,975	248,806	248,811	248,808
R^2	0.056	0.056	0.057	0.057	0.057	0.057
$F-Statistic$	(6.78)**	(22.82)***	(7.74)***	(8.33)***	(15.79)***	(7.70)***
Period	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Channel	$ETFAMISPRC$	$ETFSDMISPRC$	$ETFABSCR$	$ETFSDCR$	$ETFTURN$	$ETFSHORT$

Table 10
ETF Trading Halts on August 24, 2015

The table reports results using high-frequency second-by-second data from TAQ to estimate in a pooled regression the impact of ETF trading halts on commonality in liquidity. H is the ETF ownership-weighted average of dummy variables each reflecting a trading halt during second s in an ETF referencing stock i; $ETFOWN$ is the ETF ownership in the stock; $\Delta Illiq_{HighETF}$ is the change in the illiquidity of stocks that are in the top quartile of ETF ownership. Model 1 presents the baseline results for August 24, 2015; Model 2 shows the baseline results excluding stocks with short-sale restrictions (SSRs) or trading halts (THs) on either the NYSE or NASDAQ ; Model 3 presents the results of a falsification test which uses August 17, 2015 (the prior Monday) as a pseudo-event date. The regressions include time and stock fixed effects, and standard errors are clustered at the time (seconds) and stock level. Model 4 presents the results of an additional falsification test which estimates 1000 simulations of Model 1 using pseudo ETF halts where the ETFs affected and their halt times are randomly assigned throughout the August 24, 2015 trading day. Model 4 presents the mean of the coefficients on the 1000 simulations. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

	(1) Baseline	(2) Excluding SSRs and THs	(3) Placebo 1	(4) Placebo 2
	$\Delta illiq$	$\Delta illiq$	$\Delta illiq$	$\Delta illiq$
$H \cdot ETFOWN \cdot \Delta illiq_{HighETF}$	-21.7935***	-23.6791***	0.1680	2.0004
	(-5.53)	(-4.68)	(0.02)	(0.12)
$ETFOWN \cdot \Delta illiq_{HighETF}$	13.0186***	12.5197***	2.9154**	8.2588***
	(14.07)	(11.70)	(2.39)	(45.93)
$H \cdot \Delta illiq_{HighETF}$	1.5377***	1.4534**	0.4058	-0.2104
	(3.09)	(2.17)	(0.58)	(-0.19)
$H \cdot ETFOWN$	-0.0443	-0.0770**	-0.2268	0.0237
	(-1.26)	(-2.04)	(-1.09)	(0.25)
H	-0.0068	-0.0019	-0.0173	-0.0018
	(-1.64)	(-0.47)	(-0.72)	(-0.20)
N	8,229,545	5,763,034	8,220,493	NA
R^2	0.012	0.017	0.013	NA
Period	Aug. 24, 2015	Aug. 24, 2015	Aug. 17, 2015	Aug. 24, 2015
Fixed Effects	Time and Stock	Time and Stock	Time and Stock	Time and Stock
Clustering	Time and Stock	Time and Stock	Time and Stock	Time and Stock

Internet Appendix

Table IA.1
Baseline Regressions Using Unstandardized Ownership Variables

This table presents baseline results of regressions of commonality in liquidity $\beta_{HighETF}$ on lagged unstandardized ownership variables ($ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$). $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ are the percent ownership in a stock held by ETFs, index open-end mutual funds, active open-end mutual funds, and all other institutional investors, respectively. $\beta_{HighETF}$ measures the commonality in liquidity with respect to the illiquidity of stocks that are in the top quartile of ETF ownership as in Koch et al. (2016). Controls for the stock's market capitalization ($SIZE$) and Amihud (2002) illiquidity levels are included. In Models 1 through 3, we include each category of institutional investor separately and in Model 4 we examine include all of them together. Quarter and stock fixed-effects are included in all specifications and standard errors are double clustered by quarter and stock. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	5.4100***			5.2710***
	(9.39)			(8.57)
$INXOWN_{t-1}$		3.4350***		0.7660*
		(7.35)		(1.69)
$MFOWN_{t-1}$			0.4520***	0.2480***
			(5.43)	(3.41)
$OTHROWN_{t-1}$				0.1040*
				(1.72)
$SIZE_{t-1}$	0.0017	0.0276	0.0066	-0.0106
	(0.07)	(1.14)	(0.25)	(-0.38)
$AMIHUD_{t-1}$	-0.1190**	-0.1200**	-0.1610***	-0.1310**
	(-2.51)	(-2.33)	(-2.90)	(-2.52)
N	275,314	267,959	261,358	251,356
R^2	0.101	0.101	0.102	0.104
Period	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock

Table IA.2
ETF Ownership and Commonality in Liquidity Using Bid-Ask Spreads

This table presents baseline results of regressions of commonality in liquidity $\beta_{HighETF}$ on lagged ownership. Panel A, reports results on the effect of $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ on commonality in liquidity $\beta_{HighETF}$. $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ are the percent ownership in a stock held by ETFs, index open-end mutual funds, active open-end mutual funds, and all other institutional investors, respectively. $\beta_{HighETF}$ measures the commonality in liquidity with respect to the bid-ask spreads of stocks that are in the top quartile of ETF ownership as in Koch et al. (2016). Bid-ask spreads are constructed as the average intraday relative spread using the national best bid and offer quote at the beginning of each millisecond, weighted by the total size of all trades in this millisecond. Controls for the stock's market capitalization ($SIZE$) and average intraday relative bid-ask spreads (illiquidity proxy). In Models 1 through 3, we include each category of institutional investor separately and in Model 4 we examine include all of them together. Quarter and stock fixed-effects are included in all specifications and standard errors are double clustered by quarter and stock. Panel B, reports results with additional controls, and using only time fixed-effects. Model 1, adds β_{mxs} the stock's beta calculated using the weighted-average returns excluding the given stock on all CRSP stocks as the proxy for market returns and adds $\beta_{m,t-1}$ which is the lagged beta on the aggregate market illiquidity. Model 2 appends Model 1 with $\beta_{HighETF,t-1}$ that is the lagged value of the commonality in liquidity measure. t-statistics are reported in parentheses below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Baseline Regressions

	(1)	(2)	(3)	(4)
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	0.0661***			0.0408***
	(8.74)			(5.41)
$INXOWN_{t-1}$		0.0588***		0.0379***
		(7.94)		(5.38)
$MFOWN_{t-1}$			0.0516***	0.0287***
			(8.51)	(4.38)
$OTHROWN_{t-1}$				0.0303***
				(4.396)
$SIZE_{t-1}$	0.0430***	0.0552***	0.0377***	0.0356***
	(4.58)	(5.60)	(3.61)	(3.39)
$BIDASK_{t-1}$	1.9730**	2.0470*	1.940*	2.3050**
	(2.13)	(1.95)	(1.79)	(2.17)
N	279,769	267,004	258,386	248,534
R^2	0.065	0.066	0.066	0.068
Period	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock

Panel B: Baseline Regressions with Additional Controls

	(1)	(2)	(3)	(4)
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	0.0408***	0.0378***	0.0375***	0.0370***
	(5.41)	(4.91)	(4.96)	(4.99)
$INXOWN_{t-1}$	0.0379***	0.0376***	0.0376***	0.0379***
	(5.38)	(5.32)	(5.21)	(5.36)
$MFOWN_{t-1}$	0.0287***	0.0268***	0.0268***	0.0266***
	(4.38)	(4.04)	(4.03)	(4.07)
$OTHROWN_{t-1}$	0.0303***	0.0311***	0.0308***	0.0301***
	(4.40)	(4.57)	(4.60)	(4.59)
$SIZE_{t-1}$	0.0356***	0.0382***	0.0376***	0.0359***
	(3.39)	(3.79)	(3.65)	(3.50)
$BIDASK_{t-1}$	2.305**	2.617**	2.556**	2.4620**
	(2.17)	(2.35)	(2.39)	(2.28)
$\beta_{mxs,t-1}$		0.0132*	0.0127*	0.0124*
		(1.88)	(1.79)	(1.74)
$\beta_{m,t-1}$		-0.0087	-0.0029	-0.0006
		(-1.15)	(-0.09)	(-0.02)
$\beta_{HighETF,t-1}$				0.0122
				(1.65)
$\beta_{HighMF,t-1}$			0.0065	0.0057
			(0.22)	(0.194)
N	248,534	240,501	240,036	236,126
R^2	0.068	0.070	0.070	0.072
Period	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock