Do ETFs increase the commonality in liquidity of underlying stocks?*

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Abstract

We examine the impact of ETF ownership on the commonality in liquidity of the stocks held by ETFs, while controlling for the ownership by other institutional investors. Our results indicate that ETF ownership significantly increases the liquidity commonality on account of the arbitrage mechanism inherent in ETFs that ensures that ETF prices are in line with the prices of the underlying stocks. We show that greater arbitrage activities in both the primary and secondary markets of ETFs are associated with an increase in the effect of ETF ownership on commonality in liquidity. We exploit a quasi-natural experiment based on ETF trading halts to establish a causal relation between ETF ownership and liquidity commonality. Taken together, our results show that ETFs reduce the ability of the market participants to diversify liquidity shocks.

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Introduction

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 et al., 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 increase the volatility (Ben-David et al., 2014), reduce the liquidity (Hamm, 2010) and informational efficiency (Israeli et al., 2016), 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 important asset pricing implications. Chordia et al. (2000) and Hasbrouck and Seppi (2001) find that liquidity co-moves across securities. As with the co-movement of returns, co-movement in liquidity reduces the possibility to diversify individual asset's liquidity risk, giving rise to a liquidity risk factor. Such a factor has been shown to be priced (Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005) i.e., investors demand a risk premium for holding assets that are exposed to this factor.

We hypothesize that ETFs can increase the co-movement of liquidity through their inherent arbitrage mechanism that is designed to ensure that the difference between the prices of the ETF share and the component securities basket remains narrow. Authorized Participants (APs) attempt to arbitrage away the deviations between the ETF price and the value of the constituting basket.[2] When the ETF is trading at a premium during the day, APs sell the ETF short while simultaneously buying the basket. At the end of the 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. They unwind their positions at

[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.

[2] It is possible that arbitrage activities are not affected on an ETF-by-ETF basis as we posit but rather simultaneously across many mispriced ETFs and their constituents using netting practices and less than perfect hedges to reduce the impact of transactions costs. However, such alternative arbitrage trading strategies would lead to lower commonality in liquidity and against finding significant results. A similar argument against finding significant results applies to situations when ETFs allow or effect creation unit transactions that are primarily in-kind, primarily in-cash or some more balanced combination of in-kind and cash or when ETFs allow customized or negotiated baskets.

the end of the day by redeeming the ETF shares for the basket.[3] Additionally, high frequency traders can also take advantages of such arbitrage opportunities by taking long/short positions on the ETF and the main constituents of these ETFs. As a result, trading activity in the underlying securities is mechanically bound between them through common ETF ownership; resulting in greater commonality in liquidity between them.

We specifically address the following research questions in this paper. 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? Third, can the arbitrage mechanism explain the effect of ETF ownership on the commonality in stock liquidity? Finally, is there a causal relation between ETF ownership and commonality in stock liquidity?

We measure how the liquidity of a stock with high ETF ownership co-moves with the liquidity of other stocks that also 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 our measure of commonality in liquidity in stocks that have high ETF ownership.

Our analysis reveals several interesting findings. First, stocks having higher ETF ownership exhibit greater commonality in liquidity. This relation is not driven by small stocks alone but extends to the largest stocks. Moreover, the relation between ETF ownership and liquidity commonality is not confined to certain market conditions. We observe that the relation persists both during stressful and normal market environments. Second, the relation between ETF ownership and commonality in liquidity does not seem to be an indexing phenomenon since the ownership by index funds is explicitly controlled for in the analysis. Likewise, the commonality in liquidity that arises from ETF ownership is distinct from that arising from the ownership of active open-end mutual funds and non-mutual fund institutions. Furthermore, falsification tests

[3] Note that if APs are not closing out their positions via a primary transaction with the ETF sponsors at the end of the trading day but rather close them out in the secondary market once the price discrepancy between the ETF and constituent basket securities disappears, the additional secondary market trading in the underlying securities would create stronger commonality in liquidity effects in those stocks.

that randomly assign ETF ownership to stocks do not yield a significant relation between ETF ownership and commonality in liquidity. Next, we show that the unique arbitrage mechanism in ETFs is the underlying channel explaining the positive relation between the ETF ownership and commonality in stock liquidity. In particular, we show that during periods of greater arbitrage activity (corresponding to larger mispricing/deviation between the ETF price and the value of underlying stocks or higher level of activity in the primary and secondary market of ETFs), greater ETF flow activities (creation/redemption), greater ETF turnover, and greater shorting demand of ETF shares (due to the ability of ETFs to provide negative exposure through their share lending), we observe an increase in commonality in liquidity. This finding suggests that the underlying arbitrage mechanism in ETFs contributes to an increase in the commonality in liquidity of the stocks in the ETF portfolios.

Additionally, we follow 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. This alternative approach offers the advantage of not specifying a model to estimate the commonality in liquidity measure. However, it suffers from the limitation that it does not control for the effect of systematic market liquidity on the pairwise correlation in liquidity between two given stocks. Our findings from this complementary analysis continues to support our hypothesis that ETF ownership influences the commonality in stock liquidity.

We next establish a causal relation between ETF ownership and commonality in liquidity exploiting two quasi-natural experiments. First, we use the events of August 24, 2015 when trading was halted in certain ETFs but not in their component securities to design the experiment. Consistent with the arbitrage mechanism driving the commonality in liquidity, we find that commonality in liquidity among the underlying securities declined significantly during the ETF trading halts when the arbitrage process is interrupted. These results are robust to the exclusion of stocks that faced short-sale restrictions (SSRs) on that day. We also conduct a falsification test using 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, we use the reconstitution of Russell 1000 and Russell 2000 indexes to capture the exogenous variation in the common ETF ownership.

This in turn, 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. We also employ 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. Our results from these additional analyses further support a causal interpretation.

Our paper contributes to the broader literature examining the sources of liquidity commonality. For example, Koch et al. (2016) find that correlated trading activity by active mutual funds is a demand-side explanation of commonality in liquidity. In the case of active mutual funds, managers can have a preference for similar securities and/or possess correlated information, which can induce them to trade together to increase the commonality in liquidity. In contrast, ETFs can induce liquidity commonality through the inherent arbitrage mechanism. Moreover, the paper speaks to a large literature examining the value of indexing and its impact on the underlying securities held by the index funds (see for example, Wurgler, 2010; and Chang et al., 2015). Although index funds and most ETFs engage in passive investing, index funds unlike ETFs, do not trade continuously throughout the day and cannot be sold short. Thus, investors in index funds must wait until the end of the trading day to receive pricing updates and liquidity. Despite these differences it is interesting that both index funds and ETFs have pricing implication for the constituent securities. We contribute to this broader literature by uncovering an unintended consequence of the activities of passive investors in terms of exacerbating the commonality in liquidity of securities.

I. Data and Methodology

A. 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.[4] 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 and are consequently required to report their quarterly portfolio holdings.[5] 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 the calendar quarter. Due to daily creation and redemption, the total shares outstanding of an ETF change on a daily basis, and we therefore use updated data from Bloomberg (as such data is not reported accurately in CRSP and Compustat according to Ben-David et al. (2014)). 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, assuming that w_j, being the percent weight of each stock in the ETF portfolio is constant between fiscal period end and calendar quarter end, since most ETFs track index portfolios.

[4]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.

[5]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 observation; (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 US equity ETFs.

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.

B. 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 et al., 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 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. We take logs of the change in Amihud (2002) illiquidity measure to minimize the impact of outliers and further winsorize the final measure at the 1% and 99% percentiles for the same reason.

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

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

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 which excludes stock i (from the descriptive statistics in Table 1, stocks with ETF ownership above 4.24%). $\Delta illiq_{m,q,d}$ 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 require at least 10 days of non-missing observations to estimate the regression.

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.

II. Commonality in liquidity and ETF ownership

A. 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 the 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 disentangle 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., private funds, hedge funds, dark pools, closed-end mutual funds, etc. ($OTHROWN$). Each ownership variable is standardized prior to their inclusion in the model by demeaning the cross-sectional mean and dividing by the standard deviation, in order to facilitate the comparison of the economic significance of our results across different types of ownership. The comprehensive specification is as follows:

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

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.

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. A one standard deviation increase in ETF ownership (2.94%, see Table 1) is associated with a 6.60% increase in the commonality in liquidity. 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. To rule out the possibility that our findings are merely due to chance or are attributable to some other unobservable factors, in Table 2, panel B we conduct a set of falsification tests. Specifically, we construct a commonality in liquidity measure where we randomly assign stocks to the high ETF portfolio. Results show no significant relation between ETF ownership and this measure of commonality in liquidity constructed from the random stock portfolio.

In Table 2, panel C we include additional controls. In model 1, we repeat the baseline results in Panel A for the sake of 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 persistence in the measure. Again, $ETFOWN$ 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.[6]

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).

[6]In unreported tests we also exclude stock fixed effects in all Panel C 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 across stocks.

B. ETF Ownership and Commonality in Liquidity by Index Membership

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 all stocks as a basis of 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, we include the weight of the stock in the index it belongs to.

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

C. ETF Ownership and Commonality in Liquidity and Market Conditions

We also examine whether the relation between ETF ownership and commonality in liquidity is confined to certain market conditions. To do so, we first reestimate the baseline model excluding the crisis period 2007–2009. Panel A of Table 4 reports the results from model 2. Again, model

1 presents the results of the baseline specification as a basis 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. We also interact $ETFOWN$ with indicator variables corresponding to each period: pre-crisis, during crisis, and post-crisis and present the results in model 3. The coefficient on $ETFOWN$ interacted with an indicator variable equal to 1 for the pre-crisis period 2000–2006 ($ETFOWN \times D_{2000-2006}$) is 0.0204 and significant at the 5% level. The coefficient on $ETFOWN$ interacted with an indicator variable equal to 1 for the during-crisis period 2007–2009 ($ETFOWN \times D_{2007-2009}$) is markedly stronger at 0.0858 and is significant at the 1% level. The effect is even stronger in the post-crisis period with a coefficient on $ETFOWN$ interacted with an indicator variable equal to 1 for the post-crisis period 2010–2016 of 0.1050, which is also significant at the 1% level.

Next, we examine the magnitude of the effect in stressed market conditions by splitting the sample period into quintiles of the VIX index and reestimating the baseline model in sub-samples. We present the results in the panel B of Table 4. The coefficients on $ETFOWN$ are stable and significant across all sub-samples ranging from 0.0347 in the fourth quintile to 0.0666 in the highest VIX quintile.

Taken together, these results suggest the relation between ETF ownership and commonality in liquidity is significant across different sub-periods and is most pronounced in recent years. Moreover, the relation is robust to different market conditions.

D. 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. Specifically, 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 combinations of two different stocks in each quarter for our sample period, resulting in $550,299,832$ stock-pair-quarter observations.

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

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 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. To determine statistical significance, we triple-cluster the standard errors at the quarter, stock i, and stock j level.

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 ETF ownership. On one hand, pairwise correlation offers the advantage of not requiring a specific model to estimate the co-movement in liquidity of two stocks. On the other hand, pairwise correlation approach ignores the effect of marketwide liquidity on liquidity co-movement. Therefore, we view the two approaches as complementary to each other.

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.[7]

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 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 ($\rho_{returns}$). Antón and Polk (2014) find that stocks that are connected through common ownership exhibit higher return correlations and furthermore Avramov et al. (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). As before, we first estimate the individual effects of each institution type in models 1-3, and then their combined effect in models

[7] 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).

4 and 5. We observe 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. In the next section, we explore whether the channel 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.

III. Arbitrage 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 to the underlying basket of securities they hold, thereby providing intraday liquidity to their investors. Additionally, ETFs can be sold short which allows their inclusion in certain trading strategies that traditional funds cannot accomplish. The concurrent trading of ETFs and the securities they hold presents the challenge to uphold the law of one price. Therefore, continuously in the trading day, ETF prices are kept in line with the intrinsic value of the underlying securities through a process of formal and informal arbitrage.

Formal arbitrage happens through the APs who can take advantage of their ability to create and redeem ETF shares. If ETFs are trading at a premium relative to the net asset value 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 day, the APs then deliver the underlying securities they accumulated during the day to the ETF sponsor in exchange for newly created ETF shares in the primary market. They then 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 day until the ETF price equates its intrinsic value. At the end of the day, the APs redeem the ETF shares they accumulated in exchange for the underlying basket. They then use the basket of securities they received to cover their short positions.[8]

Informal arbitrage happens exclusively in the secondary markets by high frequency traders and hedge funds using rich/cheap convergence strategies. Essentially, these arbitrageurs buy the cheaper portfolio while simultaneously shorting the more expensive portfolio.

We examine whether the ETF arbitrage mechanism, which partly makes ETFs unique, is the source of the observed relation between commonality in liquidity and ETF ownership. We argue that if the arbitrage mechanism is responsible for this relation, then everything else equal, stocks having an ownership composed of ETFs experiencing high arbitrage intensity will exhibit a stronger commonality in liquidity than other stocks.[9]

We hypothesize that arbitrage opportunities are greater over the course of a quarter in a given stock when the ETFs that own it experience large price deviations from the underlying basket's NAV over that quarter. To this end, we develop a measure that exploits the deviation between the ETF and the underlying basket prices. The measure is calculated 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 aggregated over each quarter. We use the absolute value of the mispricing because a positive or a negative deviation from the NAV will result in arbitrage. We loosely use the word mispricing to refer to this imbalance in the ETF. The measure is then averaged 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:

[8] If APs are not closing out their positions via a primary transaction with the ETF at the end of the trading day but rather close them out in the secondary market once the price discrepancy between the ETF and constituent basket securities disappeared, commonality in liquidity across the constituent basket securities would be stronger.

[9] It is possible that arbitrage activities are not affected on an ETF-by-ETF basis as we posit but rather simultaneously across many mispriced ETFs and their constituents using netting practices and less than perfect hedges to reduce the impact of transactions costs. However, such alternative arbitrage trading strategies would lead to lower commonality in liquidity, which biases us against finding significant results. A similar argument against finding significant results applies to situations when ETFs allow or effect creation unit transactions that are primarily in-kind, primarily in-cash or some more balanced combination of in-kind and cash or when ETFs allow customized or negotiated baskets.

$$ETFAMISPRC_{i,q} = \frac{\sum_{j=1}^{J} w_{j,q-1} \times \frac{1}{D} \sum_{d=1}^{D} \left| \frac{PRC_{j,d} - NAV_{j,d}}{PRC_{j,d}} \right|}{\sum_{j=1}^{J} w_{j,q-1}} \tag{7}$$

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 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 in a given stock i at the end of the previous quarter and therefore the summation of $w_{j,q-1}$ over all ETFs in the denominator corresponds to the $ETFOWN$ measure.

We use the end of the trading day as our unit of observation for ETF mispricings. However, since both ETFs and the component stocks are trading simultaneously during the day we could alternatively compute the average mispricing at the intraday level. In fact to facilitate arbitrage, APs 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. So in theory we could create a more complete picture by matching the traded prices of ETFs to their IIVs and calculate the mispricing every 15 seconds or even at smaller intervals. This task is made difficult by the fact that ETF IIVs are not stored on TAQ, which explains our choice of using daily observations. Nonetheless, to the extent that a daily mispricing measure is coarser relative to a more refined one that would use intraday data, biases the analysis against finding significant results.

It is important to point that, in spite of arbitrage, substantial ETF mispricings can still exist. Petajisto (2013) 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 international or 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.

We present the results in Table 6. Column 1 interacts $ETFAMISPRC$ with $ETFOWN$ in the baseline specification. Prior to their inclusion in the model, and consistent with previous analyses, $ETFAMISPRC$ and all ownership variables are standardized to facilitate comparison. The results indicate that everything else equal, stocks with ETF ownership experiencing high average price deviations over the quarter exhibit an additional increase in commonality in liquidity.

The coefficient on $ETFOWN \times ETFAMISPRC$ is 0.0141 and is positive and significant at the 10% level. The coefficient on $ETFOWN$ of 0.0542 remains positive and significant at the 1% level. Economically, these results imply that a one standard deviation increase in $ETFOWN$ is associated with a 5.42% increase in commonality in liquidity, and a one standard deviation decrease in $ETFAMISPRC$ further increases the commonality in liquidity by 1.41%. These results point to arbitrage activity playing an important role in the observed increase in commonality in liquidity.

In addition to the level of mispricing $ETFAMISPRC$, we use the standard deviation of mispricing $ETFSDMISPRC$ as another proxy for the arbitrage activity. The intuition behind this alternative measure is that arbitrageurs might exhibit heterogeneity in their ability to eliminate price deviations between the ETF and the underlying basket of securities. For example, one arbitrageur may be able to close out only a fraction of the price deviation due to frictions or limits to arbitrage such as transaction costs. This in turn can prompt another arbitrageur facing lesser frictions to enter the market and further reduce the price deviation. Such a process will lead to more time-series variation in mispricing. Consistent with the arguments above, in column 2, we observe a positive coefficient of 0.0379 on the interaction between $ETFSDMISPRC$ and $ETFOWN$ that is significant at the 1% level. This finding is also economically meaningful as a one standard deviation increase in $ETFSDMISPRC$ for a given level of $ETFOWN$ is associated with an increase in the commonality in liquidity by 3.79%.

As mentioned above, ETF mispricings are resolved by arbitrageurs in both the primary and secondary markets. It is natural therefore to examine activity in those two markets as further, albeit indirect, evidence of the arbitrage process at work. In the primary markets, we use the creation and redemption activity in an ETF as a measure of its arbitrage intensity. Recall that share creation and redemption activity is part of the arbitrage mechanism conducted solely by APs. In the secondary markets, we use the turnover and short interest in an ETF as additional proxies for arbitrage intensity.

For proxies of primary market activity, we 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. We then compute the sum of the absolute value of the flows for each ETF over each quarter. We next compute for each stock, the ETF ownership-weighted average of that measure ($ETFABSFLOWS$). 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 both cases demanding liquidity to conduct these operations.

Formally, for each stock i in calendar quarter q

$$ETFABSFLOWS_{i,q} = \frac{\sum_{j=1}^{J} w_{j,q-1} \times \frac{1}{D} \sum_{d=1}^{D} \left| \frac{SHRSOUT_{j,d} - SHRSOUT_{j,d-1}}{SHRSOUT_{j,d-1}} \right|}{\sum_{j=1}^{J} w_{j,q-1}} \tag{8}$$

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 in a given stock i at the end of the previous quarter.

APs hold the exclusive right to create and redeem ETF shares and they do so for two potential reasons. First, as discussed previously. they use the creation and redemption process to maintain the ETF price in line with the price of the underlying basket. We refer to this activity conducted by the APs as formal arbitrage. However, APs sometimes create (redeem) shares to meet increasing (decreasing) market demand of the ETF. Our computed flow measure is not able to distinguish between these two reasons. However, our understanding is that it is rare that APs grow or shrink the ETF by catering to specific client needs. Most often APs will act upon an increase or decrease in demand of their product through the arbitrage mechanism. Specifically, if a given ETF is popular, the price of the ETF will reflect the increased demand creating a positive mispricing between the prices of the ETF and the underlying basket. This mispricing is reduced through the formal arbitrage mechanism resulting in the creation of more units, which is captured in the absolute flow measure $ETFABSFLOWS$ in equation 8.

Column 3 of Table 6 reports the result for the interaction variable $ETFOWN \times ETFABSFLOWS$. Again, to facilitate comparison $ETFABSFLOWS$ and all ownership variables are standardized prior to their inclusion in the model. When added to the baseline model, the interaction variable coefficient of 0.0559 is positive and significant at the 1% level. Therefore, we find that creation and redemption activity in the ETFs that own a stock induce significantly higher commonality in liquidity for that given stock.

We also use the standard deviation of ETF flows $ETFSDFLOWS$ as another proxy for arbitrage activity. This measure captures the variation in the creation or redemption of ETF shares by APs who may be doing so in response to the price deviations between the ETF and the underlying basket. In column 4, we observe a positive coefficient of 0.0228 on $ETFOWN$ interacted with $ETFSDFLOWS$ that is significant at the 1% level. This suggest that in addition to the level of flows the variation in flows influences the commonality in liquidity.

Recall that arbitrage activity can also be conducted in the secondary markets. Consequently, we create two additional proxies for such arbitrage activity – the ETF-ownership-weighted average ETF turnover and ETF short interest in each stock. We collect data on turnover ($ETFTURN$) and short interest ($ETFSHORT$) for each ETF from Bloomberg. Columns 5 and 6 of Table 6 report the results for the inclusion of the interaction variables $ETFOWN \times ETFTURN$ and $ETFOWN \times ETFSHORT$. As before, all the relevant variables are standardized prior to their inclusion in the model. We again find positive and significant coefficients when both interaction variables are included in the baseline specification.

Overall, these results suggest that the arbitrage mechanism designed to reduce pricing imbalances between ETFs and their underlying securities contributes to increasing liquidity commonality among stocks. These findings resonate well with recent theoretical and empirical evidence in Tomio (2017) who uses a different setting of cross-listed stocks and a firm's capital structure. Specifically, he finds that the intensity of arbitrage activity positively contributes to the co-movement in the liquidity of securities that trade in different markets (stocks listed in both Canada and the USA, as well as, between the debt and equity securities of the same firm). Also, Corwin and Lipson (2011) using electronic order flow data for a sample of NYSE-listed stocks find that market activities, such as arbitrage, conducted by program traders, institutional traders, retail traders, and exchange members is related to commonality liquidity.

IV. A Quasi-Natural Experiment: Events of August 24, 2017

Our results so far show that ETF ownership increases the commonality of liquidity of their underlying basket of securities and the arbitrage mechanism unique to 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 shock to the arbitrage mechanism which occurred on August 24, 2015 when trading temporarily halted on a large number of ETFs while the underlying stocks were still allowed to trade.[10]

On Monday, August 24, 2015, the U.S. equity and equity-related futures markets started the day with unusual price volatility. The December 2015, SEC Research Note, recounts the morning events as follows:[11]

- *Prior to 9:30, the most actively traded equity product–the SPDR S&P 500 ETF Trust ("SPY")–declined to more than 5% below its closing price on the previous trading day (Friday, August 21, 2015). The most actively traded equity-related futures contract–the E-Mini S&P 500 ("E-Mini")–declined to its limit down price of 5% below the previous trading day's closing price and was paused for trading from 9:25 to 9:30.*

- *At 9:30, SPY opened for regular trading hours at 5.2% below its previous day's close and then further declined to a daily low of 7.8% by 9:35. By 9:40, SPY recovered past its opening price and eventually closed down 4.2%. SPY's decline from previous day close to August 24 open was the second largest in the last decade, while SPY's decline from previous day close to August 24 daily low was the 10th largest in the last decade.*

- *From 9:30 to 9:45, more than 20% of S&P 500 companies and more than 40% of NASDAQ-100 companies reached daily lows that were 10% or more below their previous day's closing price.*

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, $illiq_{i,s}$.[12] Specifically, using every trade t reported to the consolidated tape on August 24, we calculate

[10] Approximately 300 ETFs were halted over the course of August 24, 2015 according to "ETF performance in the highly volatile equity market of August 24, 2015", Blackrock report.

[11] https://www.sec.gov/marketstructure/research/equity_market_volatility.pdf

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

$$illiq_{i,s} = \log\left[1 + \sum_{t \in s} \omega_{i,t} A_{i,t}\right] \tag{9}$$

where $\omega_{i,t}$ is the relative dollar trade size, $S_{i,t}$, of trade t within second s and $A_{i,t}$ is equal to $[|P_{i,t} - P_{i,t-1}| \cdot P_{i,t-1}^{-1}] \cdot [S_{i,t} \cdot 10^{-6}]^{-1}$ winsorized at the 99th percentile. We then estimate the following model in a pooled regression:

$$\begin{aligned}\Delta illiq_{i,s} = \alpha_i + \beta_{1,i} H_{i,s} + \beta_{2,i} H_{i,s} \cdot ETFOWN_i + \beta_{3,i} ETFOWN_i \cdot \Delta illiq_{HighETF,s} + \\ \beta_{4,i} H_{i,s} \cdot \Delta illiq_{HighETF,s} + \beta_{5,i} H_{i,s} \cdot ETFOWN_i \cdot \Delta illiq_{HighETF,s} + \beta_{6,i} ETFOWN_i \cdot \Delta illiq_{m,s} \\ + \beta_{7,i} H_{i,s} \cdot \Delta illiq_{m,s} + \beta_{8,i} H_{i,s} \cdot ETFOWN_i \cdot \Delta illiq_{m,s} + FE_{i,s} + \epsilon_{i,s}\end{aligned} \tag{10}$$

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. $\Delta illiq_{i,s}$, $\Delta illiq_{HighETF,s}$, and $\Delta illiq_{m,s}$ measure the change in the high-frequency illiquidity for a given stock (i), stocks that have high ETF ownership ($HighETF$), and the market (m), respectively.

$ETFOWN_i$ 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 fixed effects. Since we include stock and time fixed effect, we exclude the solitary terms $ETFOWN_i$, $\Delta illiq_{HighETF,s}$ and $\Delta illiq_{m,s}$ on the right-hand side of equation (10). Standard errors are two-way clustered at the stock and time level. 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 $\beta_{5,i}$ to be negative.

We present the baseline results from estimating model (10) in column 1 of Table 7. The coefficient $\beta_{5,i}$ in model (1) is -31.1208 and highly significant. A positive and significant value of 21.4123 for $\beta_{3,i}$ corroborates our earlier finding of commonality in liquidity increasing in ETF ownership. These results imply that when stocks held by those ETFs that could not be traded on August 24th, the effect of ETF ownership on the commonality of liquidity of those stocks is attenuated. This finding provides a causal interpretation supporting our hypothesis that ETF arbitrage is the underlying channel behind the relation between ETF ownership and commonality in stock liquidity.

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 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. We examine whether our results are robust to the exclusion of the stocks that experienced SSRs. The results in column 2 continue to show a negative and significant coefficient $\beta_{5,i}$, 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 a falsification test by using 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. Results in column 3 are striking. The coefficient $\beta_{5,i}$ is no longer significant, indicating that our prior findings for August 24th are not spurious.

Overall, the findings in this section underscore the causal nature of the effect of ETF ownership on commonality in liquidity of underlying stocks in the ETF basket. Specifically, we show that in periods where the arbitrage mechanism unique to ETFs is interrupted, we observe a significant weakening of this effect that helps establish the causality. Moreover, the falsification helps rule out the possibility that our findings are unlikely due to chance.

V. A Quasi-Natural Experiment: Russell Index Reconstitution

In this section, we conduct additional analyses using the Russell indexes reconstitution experiment which 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 the co-movement in liquidity of these connected stocks (as opposed to ETFs choosing to invest in stocks with 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 et al., 2015; Ben-David et al., 2014; Boone and White, 2015; Cao et al., 2015; Appel et al., 2016, among others). The Russell 1000 and 2000 stock indexes comprise the first 1000 and next 2000 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.

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 ($\rho_{\Delta liquidity,t}$) 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 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 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.

Specifically, we estimate the following regression:

$$\begin{aligned}\rho_{ij,q} = \lambda_0 + \lambda_1 ETFFCAP_{ij,q-1} + \lambda_2 ETFFCAP_{ij,q-1} \times SWITCH + \\ \lambda_3 MFFCAP_{ij,q-1} + \lambda_4 MFFCAP_{ij,q-1} \times SWITCH + \\ \lambda_5 INXFCAP_{ij,q-1} + \lambda_6 INXFCAP_{ij,q-1} \times SWITCH + CONTROLS_{ij,q-1} + \epsilon_{ij,q} \quad (11)\end{aligned}$$

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 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. To determine statistical significance, we triple-cluster the standard errors at the quarter, stock i, and stock j level.

Table 8 reports the results for the estimation of equation 11. 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.[13]

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 exonegous 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

[13] 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.

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 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 4, respectively, significant at the 5% level).

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 use an instrumental variable (IV) approach, similar to Ben-David et al. (2014) and Appel et al. (2016). In the first stage, we estimate the effect of the switches between the Russell indexes (our IV) and the common ETF ownership, and then estimate the effect of instrumented common ETF ownership on co-movement in liquidity of stocks in the 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 and a $SWITCH$ indicator variable. 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 ($\rho_{\Delta liquidity,t}$) is regressed against the predicted value of $ETFFCAP$ ($ET\widehat{FFC}AP$) and the log market capitalization of the first and second stock.[14]

Table 9 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 $ETFFCAP$ ($ET\widehat{FFC}AP$) 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

[14]In an alternative specification, we also control for the $MFFCAP$ in the first stage. We find qualitatively similar results with this alternative specification.

and liquidity commonality.

VI. 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 co-movement 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. 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. Finally, we establish a causal relation between ETF ownership and liquidity commonality through a set of quasi-natural experiments. The first experiment 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. Again a falsification test using a pseudo-event date and fictitious halts does not show any significant change in commonality in liquidity. The second experiment uses the reconstitution of Russell 1000 and Russell 2000 indexes to capture the exogenous variation in the common ETF ownership. 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.

Taken together, our paper contributes to the policy debate of widespread implications of ETFs in security markets. Specifically, we show that as ETFs continue to grow and gain higher ownership of stocks, it can reduce the ability of investors to diversify liquidity shocks due to an increase in the commonality in liquidity of stocks included in ETF portfolios.

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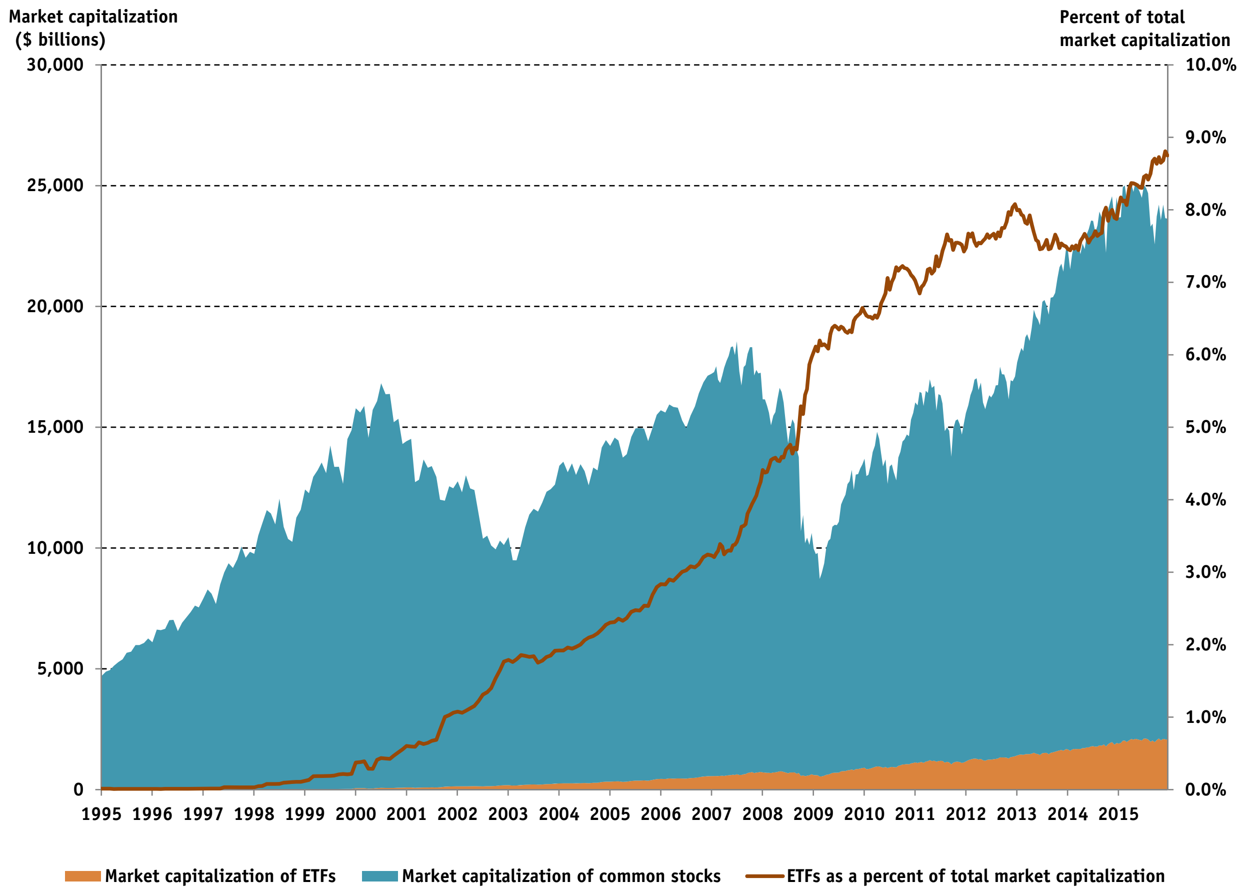

Figure 1: Assets Under Management (AUM) of ETFs trading on US stock exchanges relative to the total market capitalization of the US equity market.
Market capitalization information is obtained from CRSP on common shares (CRSP share code 10 and 11) and Exchange Traded Funds, which were identified using 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.

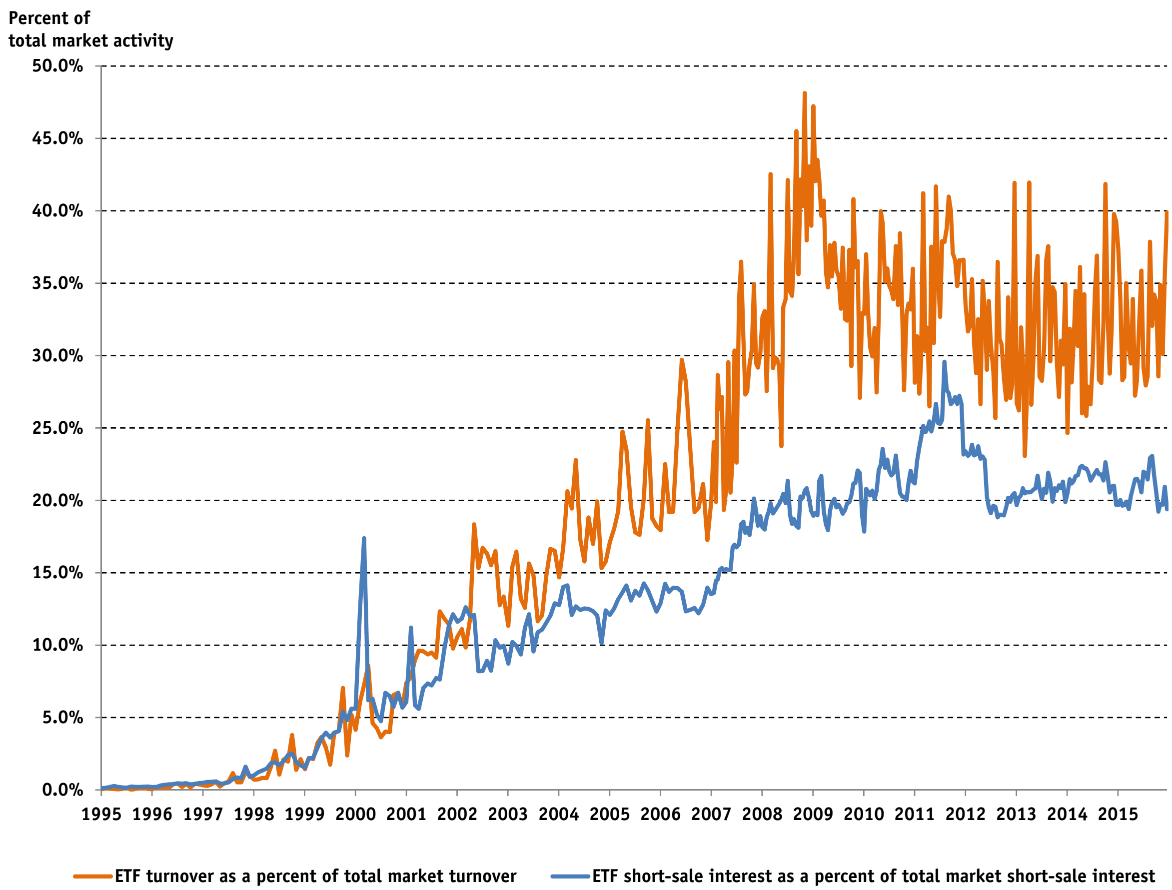

Figure 2: ETF turnover and short-sale interest as a percentage of total common share and ETF market turnover and short-sale interest (January 1995-December 2015)
Trading volume information is obtained from CRSP on common shares (CRSP share code 10 and 11) and Exchange Traded Funds, which were identified using CRSP and Compustat. Short-sale interest was obtained from Compustat on all common shares (CRSP share code 10 and 11) and Exchange Traded Funds, which were identified using CRSP and 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, 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 (mispricing) 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. $\rho_{\Delta liquidity}$ 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, passive 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, passive 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, 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 the results of falsification tests that involves repeating the baseline regressions using $\beta_{HighETF}$ estimated from a portfolio of high ETF portfolio. Panel C, 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. Models (3) through (5), report results using only quarter fixed-effects. t-statistics are reported in parenthesis 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***
	(9.933)			(8.895)
$INXOWN_{t-1}$		0.0370***		0.0128**
		(7.131)		(2.534)
$MFOWN_{t-1}$			0.0316***	0.0186***
			(5.929)	(3.728)
$OTHROWN_{t-1}$				-0.0028
				(-0.503)
$SIZE_{t-1}$	0.0239**	0.0329***	0.0196*	0.0203*
	(2.474)	(3.402)	(1.865)	(1.943)
$AMIHUD_{t-1}$	-0.0463	-0.0579*	-0.0869***	-0.0594*
	(-1.646)	(-1.982)	(-2.734)	(-1.925)
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: Placebo Regressions

	(1)	(2)	(3)	(4)
	$\beta_{Random,t}$	$\beta_{Random,t}$	$\beta_{Random,t}$	$\beta_{Random,t}$
$ETFOWN_{t-1}$				
	-0.0015			0.0029
	(-0.244)			(0.433)
$INXOWN_{t-1}$		-0.0040		-0.0075
		(-0.664)		(-1.227)
$MFOWN_{t-1}$			-0.0095	-0.0103
			(-1.494)	(-1.662)
$OTHROWN_{t-1}$				0.0022
				(0.382)
$SIZE_{t-1}$	0.0049	0.0035	0.0066	0.0077
	(0.635)	(0.434)	(0.789)	(0.891)
$AMIHUD_{t-1}$	0.0204	0.0190	0.0181	0.0220
	(0.539)	(0.477)	(0.443)	(0.528)
N	275,309	267,956	261,356	251,354
R^2	0.045	0.045	0.045	0.047
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

Continued from table 2

Panel C: Baseline Regressions with Additional Controls and Excluding Stock Fixed-Effects

	(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***
	(8.895)	(8.420)	(8.616)	(8.314)
$INXOWN_{t-1}$	0.0128**	0.0131**	0.0132**	0.0125**
	(2.534)	(2.538)	(2.532)	(2.372)
$MFOWN_{t-1}$	0.0186***	0.0188***	0.0184***	0.0188***
	(3.728)	(3.634)	(3.541)	(3.531)
$OTHROWN_{t-1}$	-0.0028	-0.0037	-0.0042	-0.0036
	(-0.503)	(-0.655)	(-0.731)	(-0.627)
$SIZE_{t-1}$	0.0203*	0.0226**	0.0229**	0.0226**
	(1.943)	(2.326)	(2.361)	(2.310)
$AMIHUD_{t-1}$	-0.0594*	-0.0555*	-0.0569*	-0.0596*
	(-1.925)	(-1.758)	(-1.796)	(-1.932)
$\beta_{mxs,t-1}$		0.0151**	0.0157**	0.0154**
		(2.264)	(2.321)	(2.306)
$\beta_{m,t-1}$		0.0192***	0.0151**	0.0157**
		(7.003)	(2.191)	(2.282)
$\beta_{HighETF,t-1}$			-0.0050	-0.0030
			(-0.685)	(-0.411)
$\beta_{HighMF,t-1}$				-0.0012
				(-0.419)
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, 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 parenthesis 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***
	(8.895)	(6.051)	(3.950)	(3.866)
$INXOWN_{t-1}$	0.0128**	0.0108*	-0.0010	-0.0158
	(2.534)	(1.821)	(-0.179)	(-0.612)
$MFOWN_{t-1}$	0.0186***	0.0196***	0.0057	0.0062
	(3.728)	(3.358)	(0.868)	(0.381)
$OTHROWN_{t-1}$	-0.0028	0.0017	-0.0063	-0.0042
	(-0.503)	(0.256)	(-0.816)	(-0.226)
$SIZE_{t-1}$	0.0203*	0.0026	0.0543***	-0.0230
	(1.943)	(0.259)	(4.334)	(-0.913)
$AMIHUD_{t-1}$	-0.0594*	-0.0709	0.1510**	3.9900
	(-1.925)	(-1.092)	(2.073)	(0.454)
$RUSELL3000.WEIGHT_{t-1}$		-18.8900		
		(-1.614)		
$RUSELL2000.WEIGHT_{t-1}$			-13.5200	
			(-0.603)	
$SP500.WEIGHT_{t-1}$				-6.7360
				(-0.698)
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 by Market Condition
Panel A, 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, 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, Panel A, Model (4). Model (2), excludes the crisis period 2007-2009 from the sample. Model (3), interacts $ETFOWN$ with pre-crisis (2000-2006), during crisis (2007-2009) and post-crisis (2010-2016) period dummies.
Panel B, reports results on the effect of $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ on commonality in liquidity β_{Liq} by quintiles of the VIX index. 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. Every specification includes time and stock fixed effects and standard errors are double-clustered by time and stock. t-statistics are reported in parenthesis below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: ETF Ownership and Commonality in Liquidity by Different Periods

	(1)	(2)	(3)
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	0.0584***	0.0566***	
	(8.895)	(7.765)	
$ETFOWN_{t-1} \times D_{2000-2006}$			0.0204**
			(2.405)
$ETFOWN_{t-1} \times D_{2007-2009}$			0.0858***
			(6.116)
$ETFOWN_{t-1} \times D_{2010-2016}$			0.1050***
			(8.548)
$INXOWN_{t-1}$	0.0128**	0.0180***	0.0154***
	(2.534)	(3.370)	(3.128)
$MFOWN_{t-1}$	0.0186***	0.0215***	0.0180***
	(3.728)	(3.930)	(3.704)
$OTHROWN_{t-1}$	-0.0028	-0.0037	0.0043
	(-0.503)	(-0.664)	(0.792)
$SIZE_{t-1}$	0.0203*	0.0173	0.0130
	(1.943)	(1.483)	(1.185)
$AMIHUD_{t-1}$	-0.0594*	-0.0357	-0.0633**
	(-1.925)	(-1.034)	(-2.079)
N	251,356	221,940	251,356
R^2	0.056	0.060	0.057
Period	2000-2016	excl. 2007-2009	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock

Panel B: ETF Ownership and Commonality in Liquidity by VIX Index Quintiles

VIX Rank	Low	2	3	4	High
	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$	$\beta_{HighETF,t}$
$ETFOWN_{t-1}$	0.0548***	0.0595**	0.0636***	0.0347*	0.0666***
	(3.912)	(2.630)	(3.721)	(2.104)	(8.687)
$INXOWN_{t-1}$	0.0155	0.0138	0.0035	0.0093	0.0187
	(1.006)	(1.366)	(0.263)	(0.865)	(1.540)
$MFOWN_{t-1}$	0.0204*	0.0443***	0.0050	0.0335**	0.0244**
	(1.849)	(3.651)	(0.518)	(2.818)	(2.550)
$OTHROWN_{t-1}$	0.0019	0.0009	-0.0030	0.0091	0.0012
	(0.151)	(0.086)	(-0.212)	(0.532)	(0.096)
$SIZE_{t-1}$	0.0443**	0.0357**	0.0224	-0.0320	0.0189
	(2.642)	(2.551)	(1.231)	(-1.179)	(0.537)
$AMIHUD_{t-1}$	-0.0664	-0.0517	-0.0161	-0.1570	-0.0042
	(-0.879)	(-0.558)	(-0.211)	(-1.791)	(-0.051)
N	52,372	49,424	49,432	47,823	45,785
R^2	0.142	0.153	0.166	0.157	0.170
Period	2000-2016	2000-2016	2000-2016	2000-2016	2000-2016
Fixed Effects	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock	Quarter & Stock
Clustering	Quarter & Stock	Quarter & Stock	Quarter & Stock	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 ($\rho_{\Delta liquidity,t}$).

Panel B, reports results on the effect of the number of ETF, passive, 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 ($\rho_{\Delta liquidity,t}$). Every specification includes quarter interacted with stock i and quarter interacted with stock j fixed effects. Standard errors are triple-clustered by quarter, stock i, and stock j. t-statistics are reported in parenthesis 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	Quarter× Stock i, and Qtr.× Stock j	Quarter× Stock i, and Qtr.× Stock j	Quarter× 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	Quarter× Stock i, and Qtr.× Stock j	Quarter× Stock i, and Qtr.× Stock j	Quarter× 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: Proxies for stock liquidity demand originating from ETFs

This table reports results on the effect of $ETFOWN$ and $ETFOWN$ interacted with proxies for ETF-induced stock liquidity demand ($\times CHANNEL$) on commonality in liquidity. $ETFOWN$, $INXOWN$, $MFOWN$ and $OTHROWN$ are the percent ownership in a stock held by ETFs, index open-end mutual funds, 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 ($AMIHUD$) are included. The proxies for ETF-induced liquidity demand are: $ETFAMISPRC$, $ETFSDMISPRC$, $ETFABSFLOWS$, $ETFSDFLOWS$, $ETFTURN$ and $ETFSHORT$. $ETFAMISPRC$ measures the ETF ownership weighted average arbitrage intensity of ETFs that hold a given stock, where arbitrage intensity 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 that daily difference over the quarter. $ETFABSFLOWS$ represents for a given stock the absolute value of daily ETF net flows (creation minus redemptions) summed over the quarter for the ETFs that hold the stock. $ETFSDFLOWS$ is the standard deviation for a given stock of the daily net flows of ETFs that own the given stock. $ETFTURN$ and $ETFSHORT$ are the ETF ownership-weighted average ETF turnover and ETF short-sale interest for a given stock. 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 parenthesis below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\beta_{HighETF,t}$	$\beta_{HighETF}$	$\beta_{HighETF}$	$\beta_{HighETF}$	$\beta_{HighETF}$	$\beta_{HighETF}$
$ETFOWN_{t-1}$	0.0542***	0.0388***	0.0312***	0.0483***	0.0428***	0.0337***
	(6.998)	(5.009)	(4.068)	(6.707)	(6.047)	(4.702)
$CHANNEL_{t-1}$	-0.0076	-0.0166**	-0.0063	-0.0096	0.0113*	0.0026
	(-1.300)	(-2.570)	(-1.015)	(-1.543)	(1.941)	(0.371)
$ETFOWN_{t-1} \times CHANNEL_{t-1}$	0.0141*	0.0379***	0.0559***	0.0228***	0.0331***	0.0514***
	(1.685)	(4.852)	(5.339)	(2.828)	(3.767)	(5.111)
$INXOWN_{t-1}$	0.0129**	0.0123**	0.0125**	0.0132**	0.0139**	0.0118**
	(2.346)	(2.266)	(2.295)	(2.459)	(2.578)	(2.167)
$MFOWN_{t-1}$	0.0190***	0.0188***	0.0164***	0.0189***	0.0181***	0.0159***
	(3.530)	(3.544)	(3.012)	(3.597)	(3.428)	(3.026)
$OTHROWN_{t-1}$	0.0002	0.0003	-0.0028	-0.0009	-0.0013	-0.0034
	(0.0416)	(0.0528)	(-0.500)	(-0.149)	(-0.230)	(-0.631)
$SIZE_{t-1}$	0.0183*	0.0177*	0.0174	0.0194*	0.0174*	0.0181*
	(1.769)	(1.674)	(1.666)	(1.856)	(1.675)	(1.745)
$AMIHUD_{t-1}$	-0.0957***	-0.0884**	-0.0718**	-0.0885**	-0.0735**	-0.0648*
	(-2.719)	(-2.486)	(-2.049)	(-2.497)	(-2.122)	(-1.899)
N	218,198	217,780	217,894	219,420	219,584	218,156
R^2	0.060	0.060	0.062	0.061	0.061	0.062
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*	*ETFABSFLOWS*	*ETFSDFLOWS*	*ETFTURN*	*ETFSHORT*

Table 7: Trading Halts

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; and $\Delta Illiq_m$ is the change in market-wide illiquidity. Model 1 presents the baseline results for August 24, 2015; model 2 shows the baseline results excluding the 2,069 stocks with short-sale restriction 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. t-statistics are reported in parenthesis below the coefficients with ***, **, and * denoting statistical significance at the 1%, 5%, and 10%, respectively.

	(1) Baseline	(2) Excluding SSRs	(3) Placebo
	$\Delta illiq$	$\Delta illiq$	$\Delta illiq$
H	-0.0079*	-0.0033	-0.0488**
	(-1.90)	(-0.80)	(-2.02)
$H \cdot ETFOWN$	-0.0305	-0.0589	-0.0094
	(-0.90)	(-1.63)	(-0.04)
$ETFOWN \cdot \Delta illiq_{HighETF}$	21.4123***	22.3701***	6.1492***
	(-16.13)	(-13.23)	(-4.42)
$H \cdot \Delta illiq_{HighETF}$	2.9007***	2.7456***	0.6989
	(-4.40)	(-3.14)	(-0.87)
$H \cdot ETFOWN \cdot \Delta illiq_{HighETF}$	-31.1208***	-33.4483***	-0.1237
	(-5.64)	(-4.91)	(-0.01)
$ETFOWN \cdot \Delta illiq_m$	-14.3114***	-16.7061***	-5.7125***
	(-9.839)	(-9.192)	(-4.276)
$H \cdot \Delta illiq_m$	-2.4036***	-2.1963***	-1.0047
	(-3.44)	(-2.72)	(-1.08)
$H \cdot ETFOWN \cdot \Delta illiq_m$	13.4625**	13.3937*	2.8282
	(1.98)	(1.69)	(0.34)
N	8,229,545	5,763,034	8,220,493
R^2	0.012	0.017	0.013
Period	Aug. 24, 2015	Aug. 24, 2015	Aug. 17, 2015
Fixed Effects	Time and Stock	Time and Stock	Time and Stock
Clustering	Time and Stock	Time and Stock	Time and Stock

Table 8: 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 ($\rho_{\Delta liquidity,t}$) 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 passive 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. t-statistics are triple-clustered at the quarter, stock i, and stock j level, and are reported in parenthesis 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

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 9: Russell Reconstitution Instrumental Variables Approach

This table reports estimates from a design exploiting the discontinuity 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 parenthesis 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 9

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)
$\widehat{ETFFCAP}$		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