ETF and Stock Price Fragility

Abstract

This paper explores the link between equity ownership by exchange-traded funds (ETFs) and stock price fragility. We show that stocks with more ETF ownership are more fragile. This positive association is more pronounced in relatively illiquid stocks. Our results suggest that due to the liquidity mismatch between stock- and ETF-level liquidity (i.e., ETFs are more liquid than stocks), when investors sell ETFs to meet liquidity needs, such non-fundamental liquidity shocks can propagate to the underlying stocks, thereby increasing stock price fragility. We also show that this liquidity mismatch effect appears in broad ETFs, but no clear evidence of it can be found in sector ETFs. We find further evidence of ETFs being used as a liquidity management tool in the fact that mutual funds tend to sell ETFs first when they experience outflow.

1. Introduction

Investors tend to sell their liquid assets first when they face liquidity needs (Scholes, 2000; Manconi, Massa, and Yasuda, 2012). Such uninformed liquidity-driven trades can bring price pressure to liquid assets, causing their stock prices to deviate from the fundamental value (Coval and Stafford, 2007). Exchange-traded funds (ETFs) are one of the most liquid assets, with large daily turnover. However, given that an ETF consists of a basket of stocks and some underlying stocks are not as liquid as the ETF itself, this paper investigates whether liquidity-driven trades of ETFs (i.e., exposure to non-fundamental shocks) increase fragility in the underlying stock prices. If this is the case, we then further investigate whether the positive association is more significant among stocks with lower liquidity relative to their ETF basket.

Prior research has explained the priority of asset sales along the liquidity spectrum. Scholes (2000) shows that fund managers sell their liquid assets first to avoid a price impact in the face of funding constraints. Building on Scholes's (2000) argument, Brown, Carlin, and Lobo (2010) build a theoretical model to show that if fund managers expect further deterioration in later periods, they end up selling their illiquid assets first. The literature on asset fire sales discusses the price pressure that liquidity-driven trading can bring to stocks. Coval and Stafford (2007) find that funds experiencing large outflows (inflows) tend to decrease (increase) their existing positions, which creates negative (positive) price pressure in overlapping holdings. Furthermore, Frazzini and Lamont (2008) find that stocks bought by funds with disproportionately high inflows underperform in the long run. Overall, liquidity-driven trading can have a detrimental price impact on liquid assets, which leads to price deviations from the fundamental value.

ETF trading has been growing rapidly in the past two decades and accounts for approximately one-third of the total trading volume in the U.S. equity market (Ben-David, Franzoni, and Moussawi, 2018). Given that most ETFs are highly liquid and able to track index returns, they can assist in liquidity management when investors face liquidity demand related to cash inflows and outflows. The literature provides some evidence that ETFs have been used to improve liquidity management by mutual funds. Sherrill, Shirley, and Stark (2017) find that more than one-third of actively managed mutual funds held an ETF at some point during their sample period. Sherrill, Shirley, and Stark (2020) further document that mutual funds holding more benchmark ETFs (highly liquid ETFs) in their portfolios tend to have lower cash holdings and a lower tracking error, especially during periods of large flows.

Since liquidity-driven trading of ETFs is unrelated to the fundamentals of the underlying stocks, we hypothesize that liquidity-driven ETF trading increases the underlying stocks' exposure to non-fundamental liquidity shocks. Particularly, we examine whether a stock with higher ETF ownership is positively associated with stock price fragility. We further predict that this effect is more pronounced among stocks with lower liquidity than the ETFs of which they are a part of because such less liquid stocks are less likely to be included in liquidity-driven trading at the stock level due to their lower liquidity.

We test the hypotheses using a comprehensive sample of U.S. stocks from 2000 to 2016. Our data for ETF funds are collected from the Center for Research in Security Prices (CRSP), Compustat, and Option Metrics. Firm-level ETF ownership is computed from the Thomson-Reuters Mutual Fund Holdings database. While it is challenging to estimate a stock's exposure to liquidity-driven ETF trades by all investors, we employ a narrower measure, the stock price fragility indicator from Greenwood and Thesmar (2011), to capture liquidity-driven trades from the correlated inflows and outflows of mutual funds. Stock price fragility is computed from the Thomson-Reuters Mutual Fund Holdings database and CRSP Mutual Fund database.

Our findings are as follows. First, our baseline regression shows a significantly positive relationship between ETF ownership and stock price fragility, which indicates that the more a stock is owned by ETFs, the more it is exposed to non-fundamental liquidity demand. Economically, a one-standard-deviation increase in ETF ownership leads to a 22.99% increase in stock price fragility relative to the unconditional mean. In a cross-sectional setting, we then examine whether the positive association between ETF ownership and stock price fragility is more pronounced among relatively illiquid stocks. We measure the relative liquidity between a stock and its ETFs by calculating the ratio of stock-level illiquidity to ETF-level illiquidity, which we call the liquidity mismatch ratio. This liquidity mismatch indicator takes a value of one if the liquidity mismatch ratio is greater than one (or its median) and zero otherwise. We regress stock price fragility on the interaction term between ETF ownership and the liquidity mismatch indicator and find a significantly positive coefficient on the interaction term. This finding is consistent with our prediction that being part of a liquid ETF increases the underlying stocks' exposure to non-fundamental liquidity demand, especially for stocks with lower liquidity.

Given that the difference between broad and sector ETFs has attracted much research attention[1], we further examine whether the positive association between ETF ownership and stock price fragility is driven by broad or sector ETF ownership. We repeat our baseline regression by decomposing ETF ownership into broad and sector ETF ownership. Our results show a positive association between broad ETF ownership and stock price fragility but a negative association between sector ETF ownership and stock price fragility. Similarly, we measure the liquidity mismatch between stocks and the broad (or sector) ETFs that they compose and regress stock price fragility on the interaction term between broad (sector) ETF ownership and liquidity mismatch indicators. Our results show a significantly positive coefficient on the interaction term between broad ETF ownership and liquidity mismatch but a insignificant coefficient on the interaction term between sector ETF and liquidity mismatch. To explain our findings, we find that since broad ETFs are more liquid than sector ETFs, stocks included in broad ETFs have greater exposure to liquidity-driven trades. Thus, stocks with higher broad ETF ownership are more fragile, especially those with lower liquidity than the broad ETFs that they compose. We also find that the negative association between sector ETF ownership and stock price fragility is not driven by the liquidity mismatch hypothesis.

We next examine the channel through which investors tend to sell ETFs for liquidity. In particular, while it is challenging to estimate the liquidity demand of all investors, we take mutual funds' activities as a narrow sample to conduct our tests. This is because we can directly observe mutual funds' liquidity demand from their regularly reported fund flow data. We construct three outflow indicators to capture the level of mutual liquidity needs: (i) a general outflow indicator, (ii) a large outflow indicator, and (iii) a small outflow indicator, capturing times when outflow is less than the mutual fund's holdings in ETFs. We then regress the percentage change in ETF holdings on the abovementioned three outflow indicators. Our results show that mutual funds tend to reduce their holdings in ETFs when they experience outflows, especially when the outflow magnitude is less than the funds' holdings in ETFs. Thus, we show that ETFs are used by mutual funds as a liquidity management tool in a way that causes fragility to propagate to individual stocks.

[1] For example, from an information perspective, Bhojraj, Mohanram, and Zhang (2020) find that broad ETFs reduce information efficiency due to irrelevant trading to a given constituent while sector ETFs improve information efficiency by facilitating information transfer. Similarly, Huang, O'Hara, and Zhong (2021) find that industry-focused ETFs facilitate short-selling and improve market efficiency. From a product perspective, Sherrill, Shirley, and Stark (2020) find that in the context of mutual fund investors, benchmark ETFs provide benefits for cash and flow management while non-benchmark ETFs provide benefits for diversification and risk reduction. Ben-David, Franzoni, and Moussawi (2021) find that broad ETFs tend to cater to cost-conscious investors, while specialized ETFs compete for the attention of unsophisticated investors.

Our study contributes to the literature in the following three ways. First, we add to the emerging literature discussing the positive and negative effects of ETFs. Some studies document benefits of using ETFs. Sağlam, Tuzun, and Wermers (2019) find that stocks with greater ETF ownership experience an increase in stock liquidity. Glosten, Nallareddy, and Zou (2020) find that ETFs can help improve information efficiency by incorporating systematic earnings news. Huang, O'Hara, and Zhong (2018) find that industry ETFs help facilitate short-selling and improve market efficiency. Lundholm (2020) finds that informed traders can use ETFs to hedge uninformed exposure and improve price informativeness. Sherrill et al. (2020) find that benchmark ETFs provide benefits for cash and flow management, while non-benchmark ETFs provide benefits for diversification and risk reduction. On the other hand, other studies document the negative effect of ETFs. For example, stocks with greater ETF ownership experience increased stock return co-movements (Da and Shive, 2018) and stock volatility (Ben-David et al., 2018) and decreased stock price informativeness and information efficiency (Israeli, Lee, and Sridharan, 2017; Bhojraj et al., 2020). We add to this literature by documenting as a negative effect of ETFs the fact that ETF ownership increases stock price fragility due to the mismatch between stock- and ETF-level liquidity.

Second, we contribute to the literature on ETF trading and non-fundamental demand shocks. Recent studies have widely explored how ETF trading propagates such shocks into the underlying securities through the arbitrage channel. Da and Shive (2018) show that when arbitrageurs simultaneously take opposite positions in an ETF and the underlying shares, the correlated trading of stocks in the same ETF can create non-fundamental shocks, resulting in excessive return co-movement in the underlying stocks. Ben-David et al. (2018) find that since ETFs attract short-horizon liquidity traders, liquidity shocks can propagate to the underlying securities through their arbitrage activities, which can increase the non-fundamental volatility of the underlying securities. Brown, Davies, and Ringgenberg (2021) find that authorized participants arbitrage by creating or redeeming ETF shares, which can signal non-fundamental demand and price future asset returns. While recent studies focus on how liquidity-driven trading of ETFs causes asset prices to deviate from their fundamental value through the arbitrage channel, our study provides an alternative channel to explain the link between liquidity-driven trading in ETFs and non-fundamental demand shocks. We identify the investor liquidity management channel, whereby stocks with greater ETF ownership are more fragile because ETFs are highly liquid assets that are well suited to meeting investors' liquidity management needs. Overall, not only the trading activities of short-horizon traders and arbitrageurs propagate non-fundamental shocks to the underlying stocks, but we add to the literature with our finding that other investors facing liquidity needs can also cause non-fundamental shocks.

Third, our findings help explain the use of ETFs by mutual funds. While the literature has widely investigated how mutual funds make investment decisions through the use of derivatives and short-selling (Koski and Pontiff, 1999; Frino, Lepone, and Wong, 2009); Chen, Desai, and Krishnamurthy, 2013, Jiao, Massa, and Zhang, 2016; Natter, Rohleder, Schulte, and Wilkens, 2016), the use of ETFs by mutual funds is underexplored. Only two papers to date have studied the consequences of and motivation behind mutual funds' use of ETFs. Sherrill et al. (2017) focus on the performance of actively managed mutual funds that hold a large position in ETFs. They show that these funds underperform due to unskilled portfolio management. Sherrill et al. (2020) show a positive association between benchmark ETF use and fund flow, suggesting that mutual funds use benchmark ETFs as cash substitutes. In particular, when mutual funds experience inflows, they tend to invest in ETFs rather than hold them as cash. While Sherrill et al. (2020) focus on funds managing inflows and use an indicator variable for ETF use, our study focuses on funds managing outflows and uses the actual percentage holdings of ETF positions in mutual funds. Our results provide more precise evidence of mutual fund liquidity management activities in that when mutual funds experience outflows, they tend to reduce their ETF positions first, especially when outflows are relatively small and can be covered by reducing current ETF positions.

The remainder of the study is organized as follows. Section 2 describes the data, variables, and our sample. Section 3 presents the empirical models and main analyses. Section 4 reports channel tests. Section 5 concludes the paper.

2. Data, variables, and sample

2.1 ETF measure

We follow Ben-David, Franzoni, and Moussawi (2018) in constructing our stock-level ETF ownership measure. We initially identify ETFs on the U.S. exchange as securities on CRSP with a share code of 73 and on Compustat or OptionMetrics with an issue of "%". We then use the Thomson-Reuters S12 database to obtain the reported equity holdings for each identified ETF. The financial information for ETFs and securities such as price and shares outstanding are collected from CRSP. We exclude ETFs that (i) consist of a mixture of different asset classes (e.g., a mixture of bonds and equity) and (ii) focus on the international equity market rather than the U.S. equity market. In total, there are 291 unique equity ETFs in the United States for the period 2000-2016 in our sample.[2]

At the stock level, ETF ownership is calculated as the total dollar value holdings by ETFs investing in the stock divided by the stock's market capitalization at the end of the quarter, as defined in Equation (1):

$$ETF_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t}}{Mkt\ Cap_{i,t}}, \tag{1}$$

where J is the set of ETFs that hold stock *i*, $w_{i,j,t}$ is the weight of the stock in the portfolio of ETF *j* in quarter *t*, and $AUM_{j,t}$ is the asset under management by ETF *j* at the end of the quarter.

2.2 Fragility measure

We follow Greenwood and Thesmar (2011) to construct stock price fragility. Our sample data are collected from the following three data sources. First, we obtain mutual equity holdings from the Thomson-Reuters S12 database. Second, we collect total net assets and fund returns from the CRSP mutual fund database to compute fund flows. We include only mutual funds with non-missing total net assets and returns in the quarter and exclude ETFs from the mutual fund sample. Third, we also obtain from CRSP stock-level data such as the price and number of shares outstanding. Consistent with Greenwood and Thesmar (2011), we limit the sample to stocks in NYSE decile 5 or greater to keep the matrix computation manageable.

At the stock level, stock price fragility captures the exposure of non-fundamental demand from mutual funds. We construct stock price fragility in four steps. First, we calculate the dollar weight ($W_{i,k,t}$) of stock *i* in mutual fund investor *k*'s portfolio at the end of quarter *t*, as defined in Equation (2):

$$W_{i,k,t} = \frac{n_{i,k,t} P_{i,t}}{\alpha_{k,t}}, \tag{2}$$

where $n_{i,k,t}$ is the number of shares *i* held by mutual fund investor *k* at the end of quarter *t*; $P_{i,t}$ is the price of share *i* at the end of quarter *t*; and $\alpha_{k,t}$ is the total portfolio value of mutual fund investor *k* at the end of quarter *t*.

Second, we compute quarterly percentage fund flows ($f_{k,t}^{\%}$) in mutual fund *k* during quarter *t*, as defined in Equation (3):

[2] Ben-David et al. (2018) identify 457 unique ETF funds for the period from 2000–2015. Our sample uses a narrower definition to screen ETFs in U.S. equity market. We tend to focus on the relatively large and liquid ETFs to investigate the liquidity mismatch issues.

$$f_{k,t}^{\%} = \frac{TNA_{k,t} - TNA_{k,t-1}(1+R_{k,t})}{TNA_{k,t}}, \tag{3}$$

where $TNA_{k,t}$ is the total net assets of mutual fund *k* at the end of quarter *t* and $R_{k,t}$ is the total return to mutual fund *k* during quarter *t*.

Third, we calculate the rolling variance-covariance matrix of percentage flow $\Omega_t^{\%}$ by taking all observations from the first quarter of 1991 to quarter *t*. We then rescale $\Omega_t^{\%}$ by fund assets in quarter *t* to estimate Ω_t, the conditional variance-covariance matrix, in Equation (4):

$$\widehat{\Omega}_t = diag(TNA_t)\Omega_t^{\%} diag(TNA_t)\ , \tag{4}$$

where TNA_t is a matrix with values equal to each mutual fund's total net assets on the diagonal elements and zero elsewhere.

Finally, we estimate stock price fragility ($G_{i,t}$) by Equation (5):

$$G_{i,t} = \left(\frac{1}{\theta_{i,t}}\right)^2 W_{i,t}'\ \Omega_t W_{i,t}, \tag{5}$$

where $W_{i,t}$ is a vector of each mutual fund investor's allocation weight to stock *i* in quarter *t*, Ω_t is the variance-covariance matrix of fund flows among mutual funds in quarter *t*, and $\theta_{i,t}$ is stock *i*'s market capitalization in quarter *t*.

2.3 Liquidity mismatch measure

Liquidity mismatch captures the difference between stock- and ETF-level liquidity. ETF liquidity refers to a stock's liquidity due to being a part of an ETF basket. Liquidity mismatch exists when a relatively less liquid stock is a component of relatively more liquid ETFs. To calculate stock-level liquidity, we collect daily price, volume, and return information from CRSP and calculate the Amihud (2002) illiquidity ($ILLIQ_{i,t}$). $ILLIQ(stock)_{i,t}$ is the average ratio of absolute daily returns to dollar volume for stock *i* during quarter *t*, as defined in Equation (6):

$$ILLIQ(stock)_{i,t} = \frac{1}{D_{i,t}} \sum \frac{|r_{i,d,t}|}{VOLD_{i,d,t}}, \tag{6}$$

where $D_{i,t}$ is the number of days for which data are available for stock *i* in quarter *t*, $r_{i,d,t}$ is the daily return of stock *i* on day *d* in quarter *t*, and $VOLD_{i,d,t}$ is the daily dollar volume of stock *i* on day *d* in quarter *t*.

To calculate ETF-level liquidity, we use the equity holding data from the Thomson-Reuters S12 database and compute the weighted average Amihud illiquidity of ETFs, weighted by the dollar weight of stock *i* held by ETF *j*, as defined in Equation (7):

$$ILLIQ(fund)_{i,t} = \sum W_{i,j,t}\, ILLIQ_{j,t}, \quad (7)$$

where $W_{i,j,t}$ is the dollar weight of stock *i* in ETF *j*'s portfolio out of the total value of ~~stock~~ ~~i~~all stocks in the set of ETFs *J* at the end of quarter *t* and $ILLIQ_{j,t}$ is the Amihud illiquidity of ETF *j* in quarter *t*.

Commented [SM1]: It doesn't consider fund size weight in constructing ILLIQ(fund)

Finally, liquidity mismatch is defined as the ratio of stock-level Amihud illiquidity to the weighted average ETF-level Amihud illiquidity, as shown in Equation (8):

$$Liquidity\ mismatch_{i,t} = \frac{ILLIQ(stock)_{i,t}}{ILLIQ(fund)_{i,t}}. \quad (8)$$

2.4 Stock-level controls

Using the data from CRSP and Compustat, we include a set of stock-level control variables. In particular, we consider the number of mutual funds (#Mfunds) that hold stock *i* during quarter *t*. Market value of equity (ME) is the market value of equity in millions. Volatility is the standard deviation of weekly stock returns over the quarter. Negative skewness is the negative skewness of weekly firm-specific stock returns over the quarter. Book-to-market is the ratio of book value of equity to market value of equity at the end of each quarter. Firm age is measured by the natural logarithm of the number of years that the stock has existed since the first effective date of link on CRSP. We also control for index and active fund ownership, which are calculated as the percentage of stock *i*'s common shares outstanding held by all index and active mutual funds in each quarter, respectively.

2.5 Descriptive statistics

In Table 1, Panel A, we present summary statistics on the main variables used in our tests. Our sample includes 80,633 stock-level quarterly observations in the U.S. over the period 2000 to 2016. Consistent with the finding of Greenwood and Thesmar (2011), stock price fragility increases over time. It has a mean of 0.0194 and a median of 0.0113, which are similar to the statistics in Friberg, Goldstein, and Hankins (2020)[3]. ETF ownership has a mean of 2.46% and a range of 0 to 10.75%.[4] We also report other characteristics of our sample. The mean liquidity

[3] Friberg, Goldstein, and Hankins (2020) find an average (median) fragility of 0.023 (0.007) with 137,208 stock-level quarterly observations from 2001 to 2017. While Friberg et al. (2020) exclude data from the utilities and financial industries, our study focuses on stocks in NYSE decile 5 or greater to keep the matrix computation manageable.
[4] Our ETF ownership measure yields values consistent with that of Ben-David et al. (2018), who find an average firm-level ETF ownership of 2.6%.

mismatch is 1.6849, with a median of 0.3332 and 75th percentile of 1.1288. We find that approximately 30% of stocks are less liquid than their ETF baskets. Our sample stock is on average held by 183 mutual funds in each quarter. The average market value and book-to-market ratio are 3.64 million and 0.5159, respectively. The sample firms on average have existed for approximately 16 years.

[Insert Table 1 about here]

3. Empirical model and results

3.1 Baseline: ETF ownership and stock price fragility

We predict that stocks with higher ETF ownership are more fragile because being included in ETFs increases stocks' exposure to liquidity-driven ETF trading. We empirically investigate the above prediction in this section. Specifically, we run Fama-Macbeth regressions[5] of stock price fragility on ETF ownership along with control variables. The regression is as follows.

$$\begin{aligned} Fragility_{i,t} &= \beta_1 ETF_{i,t} + \beta_2 Ln(\#Mfunds_{i,t}) + \beta_3 Ln(ME_{i,t}) + \beta_4 Volatility_{i,t} \\ &+ \beta_5 Negative\ skewness_{i,t} + \beta_6 BTM_{i,t} + \beta_7 Firm\ age_{i,t} \\ &+ \beta_8 Active\ fund\ ownership_{i,t} + \beta_9 Index\ fund\ ownership_{i,t} + \varepsilon_{i,t}, \qquad (9) \end{aligned}$$

where $Fragility_{i,t}$ is our proxy for exposure to non-fundamental liquidity demand, as defined in Equation (5). The key variable of interest is $ETF_{i,t}$, as defined in Equation (1). We also include an array of stock-level control variables: the number of mutual funds, market value of the security, volatility, negative skewness, book-to-market ratio, firm age, and active and index fund ownership. Regression is estimated with Newey-West standard errors with a lag length of one quarter.

Table 2 shows the regression of stock price fragility on ETF ownership shown in Equation (9). In Column (1), the coefficient (0.464) on *ETF* is positive and statistically significant at the 1% level, suggesting that an increase in ETF ownership is accompanied by an increase in stock price fragility. In Column (2), we include the control variables in the regression and show that the positive association between ETF ownership and stock price fragility is robust. Our results are also economically significant. For example, the result in Column (2) indicates that a one-standard-deviation increase in ETF ownership is positively

[5] Greenwood and Thesmar (2011) employ Fama-Macbeth regressions to account for trends of increasing fragility over the years.

related to an increase of 22.99% over the mean stock price fragility.[6] Overall, the results from Table 2 provide empirical support for our hypothesis that stocks with greater ETF ownership are more fragile due to their greater exposure to non-fundamental liquidity demand.

[Insert Table 2 about here]

3.2 Cross-sectional: Liquidity mismatch between stocks and ETFs

To add more credence to our hypothesis, we further explore whether the positive association between ETF ownership and stock price fragility is more pronounced when stocks are relatively less liquid and thereby more vulnerable to liquidity-driven ETF trades.

To examine the cross-sectional prediction, we first calculate the liquidity mismatch ratio between stock-level liquidity and ETF-level liquidity, which is the ratio of stock-level Amihud illiquidity to the weighted average ETF-level Amihud illiquidity, as defined in Equation (8). We then construct two binary liquidity mismatch indicators: (i) $High\ mismatch_{i,t}$ takes the value of one if stock *i*'s liquidity mismatch ratio is above the sample median in quarter *t* and zero otherwise. (ii) $Mismatch > 1_{i,t}$ takes the value of one if stock *i*'s liquidity mismatch ratio is greater than one in quarter *t*. A $Mismatch > 1_{i,t}$ of one indicates that stock-level liquidity is lower than ETF-level liquidity. In the regression, we augment Equation (9) by adding interaction terms (*ETF*Liquidity mismatch indicator*) and the liquidity mismatch indicators. The regression is as follows:

$$Fragility_{i,t} = \beta_1 ETF_{i,t} + \beta_2 ETF_{i,t} * Liquidity\ mismatch\ indicator_{i,t}$$
$$+\beta_3 Liquidity\ mismatch\ indicator_{i,t} + \sum_k \beta_k Controls_{i,t}^k + \varepsilon_{i,t}\ . \qquad (10)$$

Table 3 reports the regression results of the impact of liquidity mismatch on the association between ETF ownership and stock price fragility. The variable of interest is the interaction term between ETF and the liquidity mismatch indicator. In Column (1), using *High mismatch* as the liquidity indicator, we find that the interaction term (*ETF*High mismatch*) is significantly positive at the 1% level. This finding suggests that ETF ownership increases stock price fragility, especially among stocks with a higher liquidity mismatch ratio. Likewise, in Column (2), using *Mismatch>1* as the liquidity indicator, we find that the interaction term (*ETF*Mismatch>1*) is significantly positive at the 10% level. This finding suggests that ETF ownership increases stock price fragility, especially among stocks that are more illiquid than their ETF baskets. Taken together, the results from Table 3 support our argument that by being

[6] The calculation of economic significance is as follows: 22.99%=0.189*0.0236/0.0194.

included in liquid ETF baskets, a stock is exposed to greater non-fundamental liquidity demand, especially when the stock is more illiquid.

[Insert Table 3 about here]

3.3 Cross-sectional: Different effects of broad and sector ETFs

ETFs can be classified into at least two different groups: broad and sector. Broad ETFs consist of heterogeneous components tracking a broad index, while sector ETFs consist of heterogeneous components in a similar industry. Recent studies find that the two types of ETFs function in different ways and affect the market differently[7]; therefore, we further investigate whether broad and sector ETF ownership affects stock price fragility differently. Similar to our main hypothesis, we predict that when the type of ETF is relatively more liquid and more likely to be used for liquidity-driven trading, an increase in the type of ETF will drive an increase in stock price fragility.

To identify broad and sector ETFs, we manually search the titles of ETFs via Yahoo Finance and ETFdb.com to check whether the ETFs focus on specific indexes (e.g., S&P500, Russell1000) or sectors (e.g., technology, retail, financial). Our sample consists of 116 broad ETFs and 175 sector ETFs. We repeat the calculation of the liquidity mismatch ratio based on the classification of broad and sector ETFs.

In Table 1, Panel B, we report the stock-level summary statistics on broad and sector ETF ownership. Our sample considers stocks held by both broad and sector ETFs during the sample period so that we can run a regression to examine whether broad or sector ETF ownership contributes more to the increase in stock price fragility. Our sample includes 67,436 quarterly stock-level observations for the period 2000 to 2016. The average broad ETF ownership is 2.06%, while the average sector ETF ownership is 0.55%. Similar to Equation (8), we calculate the broad and sector liquidity mismatch ratio respectively. The liquidity mismatch between stock-level and broad ETF-level liquidity is 1.0940. We also find that approximately 30% of the stocks are less liquid than their broad ETF baskets. The liquidity mismatch between stock-level and sector ETF-level liquidity is 0.4724. We also find that approximately 10% of the stocks are less liquid than their sector ETF baskets.

[7] Sherrill et al. (2020) find that benchmark-tracking ETFs have been used for mutual fund liquidity management, while non-benchmark-tracking ETFs provide diversification benefits to reduce portfolio risks. Bhojraj et al. (2020) find that sector ETFs can improve stock-level information efficiency while broad ETFs cannot.

Next, we repeat the regression in Equation (9) to investigate whether the positive association between ETF ownership and stock price fragility is driven by the type of ETF ownership (broad vs. sector). We also repeat the regression in Equation (10) to examine the impact of liquidity mismatch on the positive association between the two types of ETF ownership and stock price fragility. The regression results are shown in Table 4.

[Insert Table 4 about here]

In Table 4 Column (1), we find that the coefficient (0.235) on broad ETF ownership is positive and statistically significant at the 5% level, while the coefficient (-0.222) on sector ETF ownership is negative and statistically significant at the 10% level. Economically, a one-standard-deviation increase in broad ETF ownership is positively related to an increase of 23.5% over the mean stock price fragility[8], while a one-standard-deviation increase in sector ETF ownership is related to a decrease of 9.37% from the mean stock price fragility[9].

In Table 4 Columns (2) and (3), we present the result of the impact of liquidity mismatch on the association between broad and sector ETF ownership and stock price fragility. In Column (2), the key variables of interest are the interaction terms *Broad ETF*High mismatch(broad)* and *Sector ETF*High mismatch(sector)*. We find that the coefficient on *Broad ETF*High mismatch(broad)* is positively significant at 1% level, while the coefficient on *Sector ETF*High mismatch(sector)* is insignificant. Likewise, in Column (3), we find that the coefficient on *Broad ETF* Mismatch>1(broad)* is positively significant at the 5% level, while the coefficient on *Sector ETF* Mismatch>1(sector)* is insignificant.

Overall, our results show that stocks with greater broad ETF ownership are more fragile, especially when the stocks are relatively less liquid. However, stocks with greater sector ETF ownership are less fragile, and this negative association between sector ETF ownership and stock price fragility is not driven by liquidity mismatch. We try to explain the difference in the above results. Based on our main prediction, stocks included in more liquid ETFs are more likely to be exposed to liquidity-driven trades. We then test fund-level differences between broad and sector ETFs such as liquidity, fund size, and fund age.

Table 5 presents the ETF fund-level summary statistics and univariate t-test results to compare the difference between broad and sector ETFs in our sample. We find that broad ETFs are significantly more liquid and larger than sector ETFs. On average, the Amihud illiquidity

[8] The calculations of economic significance are as follows: 23.50%=0.235*0.0192/0.0192.
[9] The calculations of economic significance are as follows: -9.37%=-0.222*0.0081/0.0192.

of broad ETFs is 0.0529, and their fund value is $3.1371 million, while the Amihud illiquidity of sector ETFs is 0.0785, and their fund value is $0.8534 million. We also find that broad ETFs have a slightly greater age than sector ETFs. On average, the age of broad ETFs is 7.26 years, while that of sector ETFs is 6.43 years. Consistent with our prediction, since broad ETFs are more liquid than sector ETFs, stocks included in broad ETFs are more likely to be exposed to liquidity-driven trades, thereby becoming more fragile.

[Insert Table 5 about here]

4. Channel tests

In the previous section, we find that stocks with higher ETF ownership are more fragile because ETFs can serve as a liquid management tool and propagate non-fundamental liquidity-driven exposure to the underlying stocks. To investigate the channel, ideally, we would capture the liquidity demand of all investors in the market and examine whether they tend to sell ETFs first when they face liquidity needs. However, estimating the liquidity demand of the universe of investors is challenging. Therefore, we choose a narrower set of investors, mutual funds, which can provide a clearer measure to capture liquidity needs. In particular, liquidity-driven trades can be inferred from investor flows into and out of funds that are less likely to be connected with information. These are observable since mutual funds regularly report their fund positions. Thus, in practice, we investigate whether mutual funds sell ETFs first when they face liquidity needs.

To measure mutual funds' liquidity needs, we construct three indicator variables to capture the level of mutual fund outflow. (i) $Outflow_{k,t}$ is a general measure that captures when a fund experiences outflow. It takes a value of one if mutual fund *k* experiences outflow in quarter *t* and zero otherwise. (ii) $Large\ outflow_{k,t}$ captures when a fund experiences large outflows such as fire sales. It takes a value of one if mutual fund *k*'s outflow is greater than the median outflow of all funds in quarter *t* and zero otherwise. (iii) $Outflow < ETF_{k,t}$ captures times when a fund experiences small outflows—in particular, when the fund's outflow is less than its ETF holdings. It takes a value of one if mutual fund *k*'s outflow is less than its percentage ETF holdings in quarter *t* and zero otherwise. We then run an OLS regression of the percentage change in ETF holdings on the outflow indicators, controlling for mutual fund size and percentage ETF holdings from the last quarter. The regression is as follows:

$$Change\ in\ ETF\ holdings_{k,t} = \beta_1 Outflow\ indicator_{k,t} + \beta_2 Fund\ size_{k,t} + \beta_3 ETF\ holding_{k,t-1} + \delta_t + \mu_k + \varepsilon_{k,t}, \quad (11)$$

where $Change\ in\ ETF\ holdings_{k,t}$ is calculated as the difference in the percentage ETF holdings in mutual fund *k* from quarter *t* to *t*-1, $Fund\ size_{k,t}$ is calculated as the logarithm of total net assets in mutual fund *k* in quarter *t*, and $ETF\ holding_{k,t-1}$ is the dollar value holdings of ETFs in mutual *k* in quarter *t*-1. Regressions are estimated with year-quarter fixed effects (δ_t), fund-level fixed effects (μ_k), and fund-clustered standard errors.

Table 6 shows the regression results of the change in ETF holdings and mutual fund outflow indicators. In Column (1), the coefficient (-0.033) on *Outflow* is negative at the 1% significance level, suggesting that mutual funds tend to reduce their holdings in ETFs when they experience outflow. In Column (2), the coefficient (-0.038) on *Large outflow* is negative at the 5% significance level, suggesting that mutual funds tend to reduce their holdings in ETFs particularly when they experience large outflow. In Column (3), the coefficient (-0.561) on *Outflow<ETF* is negative at the 1% significance level, suggesting that mutual funds tend to reduce their holdings in ETFs when their ETF holdings are large enough to cover the entire outflow. Comparing our results across the three columns, we notice that the magnitudes of the coefficients on the outflow indicators in Columns (1) and (2) are much lower than the coefficient magnitude in Column (3) and that the t-statistic on the outflow indicator in Column (3) is also greater than those in Columns (1) and (2). These findings are consistent with our expectation that when ETF holdings are large enough to offset outflow, the use of ETFs for liquidity management through a reduction in ETF holdings is more pronounced. Overall, the results provide supporting evidence that ETFs are used as a liquidity management tool by mutual funds and that mutual funds tend to reduce their ETF holdings more when they experience small outflows.

[Insert Table 6 about here]

5. Conclusion

Total assets under management of ETFs have grown rapidly in recent decades; thus, ETFs play an important role in the financial market and affect market stability. Recent studies have identified negative effects of ETFs through the arbitrage channel (Da and Shive, 2018; Ben-David et al., 2018), while our study attempts to examine the impact of ETFs on mismatch between stock- and ETF-level liquidity. In particular, we document a positive association between ETF ownership and stock price fragility. We suggest that investors tend to use ETFs for liquidity management; therefore, liquidity-driven trades of ETFs increase the underlying stocks' exposure to non-fundamental demand shocks. We further show that the position association is more pronounced in relatively illiquid stocks, indicating that the positive association is driven by the mismatch between stock- and ETF-level liquidity. We also decompose ETFs into broad and sector ETFs. Given that broad ETFs are more liquid than sector ETFs, we find a positive association between broad ETF ownership and stock price fragility, especially when there is higher liquidity mismatch; however, no clear evidence is found for sector ETF ownership. Finally, through channel tests, we show that mutual funds tend to reduce their holdings in ETFs particularly when they have enough ETF holdings to fully offset outflow, suggesting that ETFs are used as a liquidity management tool. Overall, these findings support our argument that ETFs can propagate non-fundamental liquidity demand to the underlying stocks through the liquidity mismatch channel.

Since ETFs are one of the successful financial innovations in recent decades and can be used by various investors for different purposes, we believe that future research can focus on understanding how ETFs can bring impact to the financial market stability and how different investors can use ETFs to achieve their goals.

References

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

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do ETFs increase volatility? *The Journal of Finance*, *73*(6), 2471-2535.

Ben-David, I., Franzoni, F., Kim, B., & Moussawi, R. (2021). Competition for Attention in the ETF Space (No. w28369). National Bureau of Economic Research.

Bhojraj, S., Mohanram, P., & Zhang, S. (2020). ETFs and information transfer across firms. *Journal of Accounting and Economics*, *70*(2-3), 101336.

Brown, D. B., Carlin, B. I., & Lobo, M. S. (2010). Optimal portfolio liquidation with distress risk. *Management Science*, *56*(11), 1997-2014.

Brown, D. C., Davies, S. W., & Ringgenberg, M. C. (2021). ETF arbitrage, non-fundamental demand, and return predictability. *Review of Finance*, *25*(4), 937-972.

Chen, H., Desai, H., & Krishnamurthy, S. (2013). A first look at mutual funds that use short sales. *Journal of Financial and Quantitative Analysis*, *48*(3), 761-787.

Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*(2), 479-512.

Da, Z., & Shive, S. (2018). Exchange traded funds and asset return correlations. *European Financial Management*, *24*(1), 136-168.

Frazzini, A., & Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*, *88*(2), 299-322.

Friberg, R., Goldstein, I., & Hankins, K. W. (2020). Corporate responses to stock price fragility. Working Paper.

Frino, A., Lepone, A., & Wong, B. (2009). Derivative use, fund flows and investment manager performance. *Journal of Banking & Finance*, *33*(5), 925-933.

Glosten, L., Nallareddy, S., & Zou, Y. (2021). ETF activity and informational efficiency of underlying securities. *Management Science*, *67*(1), 22-47.

Greenwood, R., & Thesmar, D. (2011). Stock price fragility. *Journal of Financial Economics*, *102*(3), 471-490.

Huang, S., O'Hara, M., & Zhong, Z. (2021). Innovation and informed trading: Evidence from industry ETFs. *The Review of Financial Studies*, *34*(3), 1280-1316.

Israeli, D., Lee, C. M., & Sridharan, S. A. (2017). Is there a dark side to exchange traded funds? An information perspective. *Review of Accounting Studies*, *22*(3), 1048-1083.

Jiao, Y., Massa, M., & Zhang, H. (2016). Short selling meets hedge fund 13F: An anatomy of informed demand. *Journal of Financial Economics*, *122*(3), 544-567.

Koski, J. L., & Pontiff, J. (1999). How are derivatives used? Evidence from the mutual fund industry. *The Journal of Finance*, *54*(2), 791-816.

Lundholm, R. J. (2021). FSA in an ETF world. *Review of Accounting Studies*, 1-28.

Manconi, A., Massa, M., & Yasuda, A. (2012). The role of institutional investors in propagating the crisis of 2007–2008. *Journal of Financial Economics*, *104*(3), 491-518.

Natter, M., Rohleder, M., Schulte, D., & Wilkens, M. (2016). The benefits of option use by mutual funds. *Journal of Financial Intermediation*, *26*, 142-168.

Sağlam, M., Tuzun, T., & Wermers, R. (2019). Do ETFs Increase Liquidity? *Available at SSRN 3142081*.

Scholes, M. S. (2000). Crisis and risk management. *American Economic Review*, *90*(2), 17-21.

Sherrill, D. E., Shirley, S. E., & Stark, J. R. (2017). Actively managed mutual funds holding passive investments: What do ETF positions tell us about mutual fund ability?. *Journal of Banking & Finance*, *76*, 48-64.

Sherrill, D. E., Shirley, S. E., & Stark, J. R. (2020). ETF use among actively managed mutual fund portfolios. *Journal of Financial Markets*, *51*, 100529.

Appendix A. Variable Definitions

This table summarizes the definitions and measurements of the dependent, independent, and control variables used in our tests. We also provide sources of data for each variable.		
Variables	Description (and *Compustat acronyms*)	Sources
Stock price fragility (G)	Following Greenwood and Thesmar (2011), stock price fragility, which measures the volatility of non-fundamental demand from mutual funds, is estimated as $$G_{i,t} = \left(\frac{1}{\theta_{i,t}}\right)^2 W'_{i,t}\,\Omega_t W_{i,t}$$ where $W_{i,t}$ is a vector of each mutual fund investor's allocation weight to stock *i* at quarter *t*; Ω_t is the variance-covariance matrix of fund flows among mutual funds at quarter *t*; $\theta_{i,t}$ is stock *i*'s market capitalization at quarter *t*.	Thomson-Reuters, CRSP
ETF	Following Ben-David, Franzoni and Moussawi (2018), ETF ownership is calculated as the sum of the ownership of all ETFs holding the stock at the end of each quarter. Using each individual ETF portfolio weight, quarterly ETF ownership in each stock of the ETF portfolio is inferred by multiplying the weight by the quarter-end ETF AUM and quarterly stock capitalization. ETF ownership in each stock is then aggregated across all ETFs that hold the stock in their portfolios. We then take the average ETF ownership from four quarters to calculate the annual ETF ownership.	Thomson-Reuters, CRSP
Broad and Sector ETF ownership	Following Bhojraj et al. (2020), we classify ETFs as broad and sector by analyzing the names of the ETFs. Particularly, we manually search the ETF names using Yahoo Finance and ETFdb.com to identify whether the ETFs focus on specific sectors (e.g., technology, retail, financial, etc.).	Yahoo Finance, ETFdb.com
Illiquidity (Amihud, 2002)	The illiquidity measure from Amihud (2002). The average ratio of absolute daily equity returns to dollar volume for stock (or ETF) *i* in quarter *t*.	CRSP
Book-to-market	The ratio of the book value of equity (*ceqq*) to market value of equity (abs(*prccq*)***cshoq*) at the end of each quarter.	CRSP/Compustat Merged
ETF age	The number of years that an ETF exists since year 1980.	Thomson-Reuters
ETF holding	The dollar value holdings of ETF in fund *k* at the end of quarter *t*.	Thomson-Reuters

ETF value	The ETF's market value is calculated as product of price and unit outstanding.	CRSP
Firm age	The natural logarithm of the number of years that the stock exists since first effective date of link (*LINKDT*).	CRSP/Compustat Merged
Fund flow	The changes in total fund assets adjusted for returns. It is estimated as $Flow_{k,t} = TNA_{k,t} - TNA_{k,t-1}(1 + R_{k,t})$ where $TNA_{k,t}$ is the total net assets of fund *k* at the end of quarter *t*, and $R_{k,t}$ is the total return of the fund *k* between quarter *t*-1 to *t*.	CRSP
Fund size	The natural logarithm of total net asset in fund *k* at the end of quarter *t*.	Thomson-Reuters, CRSP Mutual Fund,
High mismatch	An indicator variable takes value of one (zero) if the ratio of stock-level Amihud illiquidity to ETF-level Amihud illiquidity is greater (less) than its median at quarter *t*.	
Index (or active) mutual fund ownership	The percentage of firm *i*'s common shares outstanding held by all index (or active) mutual funds at the end of each quarter. Index funds are identified using the CRSP Mutual Fund database by identifying fund names containing "index", "idx ", "ind ", "indx ", "S&P", "russell", "nasdaq", "dow jones", "nyse", "SandP", "dj", "stoxx", "ftse", "wilshire", "morningstar", "msci", ""kbw", and "bloomberg".	Thomson-Reuters, CRSP Mutual Fund, MFlinks
Large outflow	An indicator variable takes a value of one if a fund's outflow is greater than the median outflow of all funds in the quarter, otherwise zero.	
Liquidity mismatch	The ratio of stock-level Amihud illiquidity to its weighted average ETF-level Amihud illiquidity, weighted by dollar value held by the ETF fund.	CRSP
Liquidity mismatch (broad)	The ratio of stock-level Amihud illiquidity to its weighted average broad ETF-level Amihud illiquidity, weighted by dollar value held by the broad ETF fund.	CRSP
Liquidity mismatch (sector)	The ratio of stock-level Amihud illiquidity to its weighted average sector ETF-level Amihud illiquidity, weighted by dollar value held by the sector ETF fund.	CRSP
Market value of equity (ME)	The natural logarithm of the market value of equity in millions [ln(*prc***shrout*)] at the end of each quarter.	CRSP
Mismatch>1	An indicator variable takes value of one (zero) if the ratio of stock-level Amihud illiquidity to ETF-level Amihud illiquidity is greater (less) than one at quarter *t*.	

Negative skewness	The negative skewness of weekly firm-specific stock return over the quarter. The weekly firm-specific stock return is estimated as the residual from the following regression: $$r_{i,t} = \alpha_i + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \varepsilon_{i,t}$$ where $r_{i,t}$ is the return on stock *i* in week *t*, and $r_{m,t}$ is the return on the CRSP value-weighted market index in week *t*.	CRSP
Number of mutual funds (#Mfunds)	The natural logarithm of the number of mutual funds that hold the stock *i* during quarter *t*.	Thomson-Reuters
Outflow	An indicator variable takes a value of one if fund flow is less than zero in the quarter, otherwise zero.	
Outflow<ETF	An indicator variable takes a value of one if a fund's outflow is less than its percentage of ETF holding in the quarter, otherwise zero.	
Volatility	The standard deviation of weekly stock returns over the quarter.	CRSP

Table 1. Descriptive statistics

This table provides descriptive statistics for the variables in our quarterly sample of large U.S. publicly traded firms from 2000 to 2016. The table presents the means, standard deviations, and different percentiles (25^{th}, 50^{th}, and 75^{th}) for all variables used in the analysis of ETF ownership, liquidity mismatch, and fragility. Panel A reports descriptive statistics for the overall sample, and Panel B reports the descriptive statistics for the sample of broad and sector ETF ownership. Fragility is a measure of stock-level exposure to non-fundamental demand shocks calculated using mutual fund ownership and flow variance-covariance. ETF is computed as the sum of ownership of all ETFs holding the stock at the end of each quarter. Liquidity mismatch is calculated as the ratio of the stock-level Amihud illiquidity to the weighted average ETF-level Amihud illiquidity, weighted by the dollar value held by the ETF fund. Control variables include the number of mutual funds, market value, volatility, negative skewness, book-to-market ratio, firm age, and active and index fund ownership. All variables are winsorized at the 1^{st} and 99^{th} percentiles. All variable definitions are provided in Appendix A.

Panel A: Descriptive statistics for the overall sample

N=80,663

Variable	Mean	SD	P25	Median	P75
Fragility	0.0194	0.0357	0.0046	0.0113	0.0250
ETF	0.0246	0.0236	0.0057	0.0187	0.0351
Liquidity mismatch	1.6849	4.6312	0.1054	0.3332	1.1288
Ln(#Mfunds)	5.2091	0.7601	4.8203	5.2730	5.7236
Ln(ME)	1.2919	1.2581	0.3283	1.0664	2.0802
Volatility	0.0212	0.0119	0.0132	0.0181	0.0255
Negative skewness	-0.2155	1.3296	-1.2596	-0.2951	0.8094
Book-to-market	0.5159	0.3433	0.2810	0.4570	0.6812
Firm age	2.7849	0.9148	2.1972	2.9444	3.5835
Active fund ownership	0.2073	0.1012	0.1373	0.2055	0.2735
Index fund ownership	0.0252	0.0202	0.0116	0.0222	0.0338

Panel B: Descriptive statistics for sample of broad and sector ETF ownership

N=67,436

Variable	Mean	SD	P25	Median	P75
Broad ETF	0.0206	0.0192	0.0062	0.0170	0.0280
Sector ETF	0.0055	0.0081	0.0004	0.0021	0.0070
Liquidity mismatch (broad)	1.0940	1.8488	0.1690	0.4439	1.1628
Liquidity mismatch (sector)	0.4724	1.3760	0.0368	0.1022	0.2929
Fragility	0.0192	0.0249	0.0052	0.0120	0.0255

Table 2. ETF ownership and stock price fragility

This table presents the estimated coefficients from Fama-Macbeth regressions explaining the association between ETF ownership and stock price fragility, along with other control variables. Our sample covers the 2000-2016 period. The dependent variable is stock price fragility, which measures stock-level exposure to non-fundamental demand shocks calculated using mutual fund ownership and flow variance-covariance. ETF is computed as the sum of ownership of all ETFs holding the stock at the end of each quarter. Other control variables include the number of mutual funds, market value of equity, volatility, negative skewness, book-to-market ratio, firm age, and active and index fund ownership. All tests compute heteroscedasticity- and autocorrelation-consistent Newey-West (1987) standard error estimates with a lag length of one quarter. All variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Appendix A. Robust t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable =	Stock price fragility	
Variable	(1)	(2)
ETF	0.464***	0.189***
	(4.96)	(2.73)
Ln(#Mfunds)		-0.015***
		(-10.82)
Ln(ME)		0.002***
		(3.48)
Volatility		-0.021
		(-1.22)
Negative skewness		0.000*
		(1.87)
Book-to-market		0.001**
		(2.30)
Firm age		0.001***
		(3.50)
Active fund ownership		0.196***
		(25.94)
Index fund ownership		0.160***
		(3.38)
Observations	80,663	80,663
R-squared	0.026	0.415
Number of groups	64	64
Fama-Macbeth	Y	Y

Table 3. ETFs, liquidity mismatch, and stock price fragility

This table presents the estimated coefficients from regressions explaining the association between ETF ownership, liquidity mismatch, and stock price fragility. We report Fama-MacBeth estimates, which are equal weighted quarter by quarter. Our sample covers the 2000-2016 period. The dependent variable is stock price fragility, which measures stock-level exposure to non-fundamental demand shocks calculated using mutual fund ownership and flow variance-covariance. ETF is computed as the sum of ownership of all ETFs holding the stock at the end of each quarter. There are two measures of liquidity mismatch: High mismatch and Mismatch>1. High mismatch is an indicator variable taking the value of one (zero) if the ratio of stock-level Amihud illiquidity to ETF-level Amihud illiquidity is greater (less) than its median in quarter *t*. Mismatch>1 is an indicator variable taking the value of one (zero) if the ratio of stock-level Amihud illiquidity to ETF-level Amihud illiquidity is greater (less) than one in quarter *t*. Other control variables include the number of mutual funds, market value of equity, volatility, negative skewness, book-to-market ratio, firm age, and active and index fund ownership. All tests compute heteroscedasticity- and autocorrelation-consistent Newey-West (1987) standard error estimates with a lag length of one quarter. All variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Appendix A. Robust t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable =	Stock price fragility	
Variable	(1)	(2)
ETF* High mismatch	0.187***	
	(3.75)	
ETF* Mismatch>1		0.086*
		(1.70)
ETF	0.035	0.086*
	(0.77)	(1.90)
High mismatch	0.000	
	(0.06)	
Mismatch>1		0.003***
		(4.69)
Ln(#Mfunds)	-0.015***	-0.015***
	(-11.29)	(-11.05)
Ln(ME)	0.002***	0.002***
	(4.75)	(4.53)
Volatility	-0.013	-0.022
	(-0.75)	(-1.31)
Negative skewness	0.000*	0.000*
	(1.81)	(1.91)
Book-to-market	0.001**	0.001**
	(2.29)	(2.31)
Firm age	0.001***	0.001***
	(2.82)	(3.45)
Active fund ownership	0.197***	0.198***
	(26.81)	(26.07)
Index fund ownership	0.165***	0.165***
	(3.34)	(3.43)
Observations	80,663	80,663
R-squared	0.418	0.418
Number of groups	64	64
Fama-Macbeth	Y	Y

Table 4. Broad vs. sector ETFs, liquidity mismatch, and stock price fragility

This table presents the estimated coefficients from regressions explaining the association between broad vs. sector ETF ownership, liquidity mismatch, and stock price fragility. We report Fama-MacBeth estimates, which are equal weighted quarter by quarter, and t-statistics in parentheses. Our sample covers the 2000-2016 period. The dependent variable is stock price fragility, which measures stock-level exposure to non-fundamental demand shocks calculated using mutual fund ownership and flow variance-covariance. We classify ETF ownership into two types: broad and sector ETF ownership, which are calculated as the sum of ownership of broad (or sector) ETFs holding the stock at the end of each quarter. There are two measures of liquidity mismatch: High mismatch and Mismatch>1. High mismatch(broad) is an indicator variable taking the value of one if the ratio of stock-level Amihud illiquidity to the weighted average broad ETF-level Amihud illiquidity is greater than its median in quarter *t* and zero otherwise. High mismatch(sector) is an indicator variable taking the value of one if the ratio of stock-level Amihud illiquidity to the weighted average sector ETF-level Amihud illiquidity is greater than its median in quarter *t* and zero otherwise. Mismatch>1(broad) is an indicator variable taking the value of one if the ratio of stock-level Amihud illiquidity to the weighted average broad ETF-level Amihud illiquidity is greater than one in quarter *t* and zero otherwise. Mismatch>1(sector) is an indicator variable taking the value of one if the ratio of stock-level Amihud illiquidity to the weighted average sector ETF-level Amihud illiquidity is greater than one in quarter *t* and zero otherwise. Other control variables include the number of mutual funds, market value of equity, volatility, negative skewness, book-to-market ratio, firm age, and active and index fund ownership. All tests compute heteroscedasticity- and autocorrelation-consistent Newey-West (1987) standard error estimates with a lag length of one quarter. All variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided in Appendix A. Robust t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable =		Stock price fragility	
Variable	(1)	(2)	(3)
Broad ETF	0.235**	0.144	0.093*
	(2.54)	(1.48)	(1.81)
Sector ETF	-0.222*	-0.120	-0.161
	(-1.84)	(-0.61)	(-1.22)
Broad ETF* High mismatch(broad)		0.134***	
		(3.85)	
Sector ETF* High mismatch(sector)		-0.336	
		(-1.26)	
High mismatch(broad)		0.000	
		(0.88)	
High mismatch(sector)		0.002***	
		(4.63)	
Broad ETF* Mismatch>1(broad)			0.251**
			(2.24)
Sector ETF* Mismatch>1(sector)			-0.005
			(-0.02)
Mismatch>1(broad)			0.001
			(1.56)
Mismatch>1(sector)			0.003***
			(3.43)
Ln(#Mfunds)	-0.016***	-0.015***	-0.015***
	(-15.51)	(-15.03)	(-14.88)
Ln(ME)	0.002***	0.002***	0.002***
	(3.96)	(4.37)	(4.34)
Volatility	-0.029	-0.023	-0.032*
	(-1.60)	(-1.28)	(-1.82)
Negative skewness	0.000	0.000	0.000
	(1.18)	(1.15)	(1.27)
Book-to-market	0.001	0.001	0.001
	(1.63)	(1.30)	(1.25)
Firm age	0.000*	0.000**	0.000*
	(1.90)	(2.12)	(1.88)
Active fund ownership	0.175***	0.175***	0.175***
	(61.15)	(60.69)	(60.28)
Index fund ownership	0.182***	0.175***	0.177***
	(3.22)	(3.14)	(3.32)
Observations	67,436	67,436	67,436
R-squared	0.490	0.495	0. 497
Number of groups	64	64	64
Fama-Macbeth	Y	Y	Y

Table 5. Broad vs. sector ETF characteristics

This table presents summary statistics for three characteristics of the broad and sector ETFs in our sample and univariate t-test results explaining the difference between broad and sector ETFs. Our sample covers 11,386 fund-quarter observations during the period 2000-2016. Illiquidity is a measure from Amihud (2002) calculated as the daily ratio of absolute stock return to the dollar volume, averaged over a quarter. ETF value is the market value (in millions) of the ETF fund. ETF age is the number of years that the fund has existed in the Thomson Reuters mutual fund database starting from 1980. All variable definitions are provided in Appendix A. T-tests are conducted to test for differences in the means of the two subsamples, and robust t-statistics are presented in parentheses. ***, **, and * denote significance at the 0.1%, 1%, and 5% levels, respectively.

	Broad ETF (5055 observations)		Sector ETF (6331 observations)		Difference	T-statistics
Variable	Mean	SD	Mean	SD		
Illiquidity	0.0529	0.1282	0.0785	0.2211	-0.0256***	(-7.72)
ETF value	3.1371	12.5307	0.8534	1.9164	2.284***	(12.83)
ETF age	7.2617	5.1073	6.4349	4.5533	0.827***	(9.00)

Table 6. Mutual fund outflow and change in ETF holdings

This table presents the estimated coefficients from regressions explaining the association between mutual fund outflow and the percentage change in ETF holdings. Our sample covers the 2000-2016 period and 2,804 unique mutual funds. The dependent variable is the change in ETF holdings in mutual fund *k* during quarter *t*, which is calculated as the difference in ETF holding divided by the total fund value from quarter *t*-1 to quarter *t*. We construct three indicator variables to capture the level of mutual fund outflow. *Outflow* takes the value of one if the fund flow is less than zero in the quarter and zero otherwise. *Large outflow* takes the value of one if the fund outflow is greater than the median outflow of all funds in the quarter and zero otherwise. *Outflow<ETF* takes a value of one if the fund's outflow is less than its percentage ETF holdings in the quarter and zero otherwise. Fund size is calculated as the natural log of total net assets in the fund. Lag ETF holding is the dollar value ETF holdings in the quarter *t*-1. All variable definitions are provided in Appendix A. All regressions are estimated with fund-level and year-quarter fixed effects and fund-clustered standard errors. Robust t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable =	Change in ETF holdings (%)		
Variable	(1)	(2)	(3)
Outflow	-0.033***		
	(-4.54)		
Large outflow		-0.038***	
		(-5.10)	
Outflow<ETF			-0.561***
			(-17.45)
Fund size	0.046***	0.045***	0.041***
	(11.34)	(11.27)	(9.95)
Lag ETF holding	-0.000***	-0.000***	-0.000***
	(-24.02)	(-24.07)	(-21.96)
Observations	97,686	97,686	97,686
Adjusted R-squared	0.051	0.051	0.065
Fund-level F.E.	Y	Y	Y
Year-quarter F.E.	Y	Y	Y