Exchange Traded Funds and Stock Price Fragility

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Abstract: This paper examines the relationship between exchange-traded fund (ETF) ownership and stock price fragility. We find that stocks with higher ETF ownership are more fragile, primarily due to a liquidity mismatch between ETFs and their underlying stocks, with ETFs being more liquid. When investors utilize ETFs for liquidity management, non-fundamental liquidity shocks are propagated to underlying stocks, exacerbating their price fragility. These effects are stronger in more illiquid stocks and are most evident among broad ETFs rather than sector ETFs. To establish causality, we employ three identification strategies: (1) using Russell index reconstitution as an instrumental variable, (2) analyzing BlackRock's acquisition of Barclays' iShares ETF platform as a natural experiment, and (3) considering staggered ETF initiations as exogenous shocks. We also examine the COVID-19 pandemic as a recent liquidity shock. Our findings align with the "reverse flight to liquidity" phenomenon, where highly liquid assets face significant selling pressure during crises.

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Keywords: ETF ownership, Stock price fragility, liquidity mismatch, mutual funds

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1. Introduction

Liquidity is the cornerstone of financial markets, influencing asset prices and trading behavior. Investors often prioritize liquid assets to meet immediate cash needs, particularly during periods of financial stress. This behavior underpins the "reverse flight to liquidity" phenomenon, where highly liquid assets, paradoxically, experience significant selling pressure during crises (Ma, Xiao, and Zeng, 2022). Exchange-traded funds (ETFs), among the most liquid assets with high daily turnover, are increasingly used by investors to manage liquidity demands (Khomyn, Putniņš, and Zoican, 2024). However, ETFs hold baskets of stocks, some of which are far less liquid than the ETFs themselves. This raises an important question: does liquidity-driven trading of ETFs propagate non-fundamental liquidity shocks to the underlying stocks, thereby increasing their stock price fragility (Greenwood and Thesmar, 2011)?

Prior research extensively examines the prioritization of asset sales along the liquidity spectrum. Scholes (2000) shows that fund managers typically sell their liquid assets first to minimize price impact under funding constraints. Building on this, Brown, Carlin, and Lobo (2010) develop a theoretical model to show that if further deterioration is expected, fund managers may opt to sell liquid assets first. The literature on asset fire sales highlights the significant price pressures caused by liquidity-driven trading. Coval and Stafford (2007) find that funds experiencing large outflows or inflows adjust their positions, creating negative or positive price pressures on overlapping holdings. Similarly, Frazzini and Lamont (2008) show that stocks acquired by funds with disproportionately high inflows underperform in the long run. While high-quality liquid assets typically experience net buying pressures, they may also exhibit unusual net selling pressures during crises (Ma, Xiao, and Zheng, 2022). Collectively, these studies emphasize the critical role of liquidity-driven trading in causing price deviations from the fundamental values.

In parallel, ETF trading has grown exponentially over the past two decades, now accounting for approximately one-third of the total trading volume in the U.S. equity market (Ben-David, Franzoni, and Moussawi, 2018). In general, ETFs are highly liquid instruments that track index returns, making them valuable tools for liquidity management during cash inflows and outflows. Existing research provides evidence of ETFs being utilized by mutual funds to manage liquidity. Sherrill, Shirley, and Stark (2017) find that more than one-third of actively managed mutual funds held ETFs in their portfolios during their sample period, and mutual funds with higher allocations to benchmark ETFs tend to maintain lower cash holdings.

Given that liquidity-driven trading of ETFs is often unrelated to the fundamentals of the underlying stocks, we hypothesize that such liquidity-driven ETF trading increases the exposure of these underlying stocks to non-fundamental liquidity shocks, thereby amplifying their price fragility. Particularly, we examine whether stocks with higher ETF ownership exhibit greater stock price fragility and whether this effect is more pronounced for stocks with lower liquidity relative to their ETF basket. This liquidity mismatch, where ETFs are more liquid than their underlying stocks, exacerbates price pressure on less liquid stocks during liquidity-driven ETF sales. To the best of our knowledge, this is the first paper to study how liquidity shocks originating from trading ETFs propagate to their underlying stocks and increase stock price fragility.

Using a comprehensive sample of U.S. stocks from 2000 to 2023, we test our hypotheses With data from the Center for Research in Security Prices (CRSP), Compustat, and Option Metrics. Firm-level ETF ownership is computed using the Thomson-Reuters Mutual Fund Holdings database. We measure stock price fragility using the methodology developed by Greenwood and Thesmar (2011), which captures liquidity-driven trading stemming from correlated mutual fund inflows and outflows. Our baseline regression shows a significant positive association between ETF ownership and stock price fragility, supporting the view that stocks owned by ETFs are more vulnerable to non-fundamental liquidity shocks.

Potential endogeneity concerns from confounding factors, such as omitted variables that correlate with both ETF ownership and stock price fragility, may render our findings spurious. For instance, authorized participants' (AP) activities in ETF creation and redemption may influence secondary market trading of ETFs and individual stocks. To address potential endogeneity concerns, we employ three identification strategies.

First, we leverage the annual reconstitution of the Russell 1000 and 2000 indexes, which generates exogenous variations in ETF ownership near the index cutoff (Ben-David, Franzoni, and Moussawi, 2018; Coles, Heath, and Ringgenberg, 2022). Using an instrumental variable (IV) approach, we confirm that index-driven changes in ETF ownership significantly influence stock price fragility. Second, following Antoniou, Li, Liu, Subrahmanyam, and Sun (2023) and Zou (2019), we examine the 2009 acquisition of Barclays Global Investors by BlackRock as a positive exogenous shock to ETF ownership, using a difference-in-difference (DiD) framework. We find that firms with higher pre-acquisition iShares ETF ownership exhibit significantly increased price fragility post-acquisition compared to matched control firms. Third, following Bhojraj, Mohanram, and Zhang (2020), we analyze staggered ETF initiations, showing that stock price fragility rises significantly within four quarters of an ETF's initiation.

Our cross-sectional analyses confirm that the positive relationship between ETF ownership and stock price fragility is amplified for stocks with greater liquidity mismatches relative to their ETFs. Additionally, we differentiate between broad and sector ETFs, finding that the liquidity mismatch effect is primarily driven by broad ETFs, which are inherently much more liquid.[1] Sector ETFs, by contrast, do not exhibit this effect, highlighting the distinct roles of ETF types in propagating liquidity shocks.

Our results further reveal that the impact of ETF ownership on stock price fragility intensifies during periods of heightened liquidity shocks, such as the COVID-19 pandemic. The pandemic triggered significant selling pressure on ETFs, reflecting the “reverse flight to liquidity” phenomenon, whereby investors offload highly liquid assets during times of market turmoil (Ma, Xiao, and Zeng, 2022). Our analysis shows that the relationship between ETF ownership and stock price fragility was significantly stronger during the COVID-19 period than in non-pandemic periods, underscoring how liquidity-driven ETF trading magnifies price pressures on individual stocks during market crises.

Finally, we examine how mutual funds utilize ETFs for liquidity management. Using fund flow data, we demonstrate that mutual funds experiencing outflows tend to reduce their ETF holdings first, especially when the scale of outflows can be accommodated by liquidating ETFs. This behavior underscores the use of ETFs as liquidity management tools, contributing to price fragility in less liquid underlying stocks.

Our study makes three key contributions to the literature: First, we contribute to the emerging literature on the positive and negative effects of ETFs by focusing on an underexplored aspect: liquidity mismatches and the transmission of liquidity shocks from ETFs to their underlying stocks. Prior research predominantly examines ETFs’ role in information efficiency. For instance, Glosten, Nallareddy, and Zou (2020) find that ETFs improve information efficiency by enabling systematic earnings news to be incorporated more quickly across stocks. Similarly, Huang, O’Hara, and Zhong (2018) show that industry ETFs facilitate hedging and improve market efficiency, while Lundholm (2020) demonstrates that ETFs help

[1] 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.

informed traders hedge uninformed exposure, enhancing price informativeness. However, other studies identify negative effects such as increased stock return co-movement (Da and Shive, 2018), elevated stock volatility (Ben-David, Franzoni, and Moussawi, 2018), and reduced price informativeness (Israeli, Lee, and Sridharan, 2017; Bhojraj, Mohanram, and Zhang, 2020). These effects arise because ETFs attract uninformed (noisy) traders and lead to greater informational opacity. We extend this literature by documenting a new negative effect: ETF ownership increases stock price fragility by transmitting non-fundamental liquidity shocks from ETFs to their less liquid underlying stocks due to liquidity mismatches.

Second, we contribute to the literature on ETF trading and non-fundamental demand shocks by identifying an investor liquidity management channel. Prior studies mainly focus on the arbitrage channel, where the linkage between ETFs and the underlying stocks is through arbitrage activities. For instance, Da and Shive (2018) show that arbitrageurs' correlated trades in ETFs and underlying stocks create excessive return co-movements, while Ben-David, Franzoni, and Moussawi (2018) find that short-horizon traders amplify non-fundamental volatility. Brown, Davies, and Ringgenberg (2021) further highlight how authorized participants' arbitrage activities can signal non-fundamental demand. In contrast, our study identifies a distinct mechanism: liquidity-driven trading by investors, particularly those institutional investors subject to outflows, propagates non-fundamental shocks to stocks with higher ETF ownership, increasing their stock price fragility.

Third, our findings provide new insights into mutual funds' strategic use of ETFs as liquidity buffers, an area that has received limited attention. While studies have examined mutual funds' use of derivatives and short-selling (Koski and Pontiff, 1999; Frino, Lepone, and Wong, 2009; Chen, Desai, and Krishnamurthy, 2013), only a few have investigated their ETF usage. Sherrill, Shirley, and Stark (2020) show that mutual funds use benchmark ETFs as cash substitutes during inflows, while those funds holding ETFs underperform due to portfolio management inefficiencies (Sherrill, Shirley, and Stark, 2017). Our study complements their work by focusing on funds managing outflows. We show that mutual funds tend to sell ETFs first to meet liquidity needs, which highlights ETFs' role in liquidity management but also underscores the unintended consequence of increasing stock price fragility.

The remainder of the study is organized as follows. Section 2 describes the data and main variables. Section 3 presents empirical analyses. Section 4 concludes the paper.

2. Data and variables

2.1 ETF measure

We 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 2,546 unique equity ETFs in the United States for the period 2000-2023 in our sample.[2]

To construct ETF ownership, we employ two methods from literature. In the first measure, we follow Israeli, Lee, and Sridharan (2017, hereafter *ils*) and define the *ETF (ils)* of stock *i* in quarter *t* as the aggregate number of shares held by all ETFs divided by the total number of shares outstanding at the end of the quarter, as defined in Equation (1):

$$ETF(ils) = \frac{Shares\ held\ by\ all\ ETF_{i,t}}{Total\ share\ outstandings_{i,t}}. \quad (1)$$

[2] Ben-David, Franzoni, and Moussawi (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, by focusing on the relatively large and liquid ETFs to investigate the liquidity mismatch issues.

In the second measure, we follow Ben-David, Franzoni, and Moussawi (2018, hereafter *bfm*) and define *ETF(bfm)* of stock *i* in quarter *t* as the sum of the dollar value of holdings by all ETFs investing in the stock divided by the stock's market capitalization at the end of the quarter, which is defined in Equation (2):

$$ETF(bfm) = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t}}{Mkt\ Cap_{i,t}}, \tag{2}$$

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 assets 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 fund 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 obtain stock-holding level data, such as the price and number of shares outstanding, from CRSP. 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 (3):

$$W_{i,k,t} = \frac{n_{i,k,t} P_{i,t}}{\alpha_{k,t}}, \tag{3}$$

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 (4):

$$f_{k,t}^{\%} = \frac{TNA_{k,t} - TNA_{k,t-1}(1+R_{k,t})}{TNA_{k,t}}, \tag{4}$$

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 the 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 $\widehat{\Omega}_t$, the conditional variance-covariance matrix, in Equation (5):

$$\widehat{\Omega}_t = diag(TNA_t)\Omega_t^{\%}diag(TNA_t), \tag{5}$$

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 (6):

$$G_{i,t} = \left(\frac{1}{\theta_{i,t}}\right)^2 W_{i,t}' \, \widehat{\Omega}_t W_{i,t}, \tag{6}$$

where $W_{i,t}$ is a vector of each mutual fund's allocation weight to stock *i* in quarter *t*, $\widehat{\Omega}_t$ is the conditional 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*. $W_{i,t}' \, \widehat{\Omega}_t W_{i,t}$ captures the risk contribution of each stock to the portfolio by taking into account both the fund flows (from $\widehat{\Omega}_t$) and the allocation weights of each fund to each stock (from $W_{i,t}'$ and $W_{i,t}$).

2.3 Liquidity mismatch measure

Liquidity mismatch captures the difference between stock- and ETF-level liquidity. Liquidity mismatch exists when a less liquid stock is a component of 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 (7):

$$ILLIQ(stock)_{i,t} = 10^6 \frac{1}{D_{i,t}} \sum \frac{|r_{i,d,t}|}{VOLD_{i,d,t}}, \quad (7)$$

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 first identify ETFs in CRSP and calculate the Amihud (2002) illiquidity ($ILLIQ\ (etf)_{j,t}$). $ILLIQ\ (etf)_{j,t}$ is the average ratio of absolute daily returns to dollar volume for fund *j* during quarter *t*, as defined in Equation (8):

$$ILLIQ(etf)_{j,t} = 10^6 \frac{1}{D_{j,t}} \sum \frac{|r_{j,d,t}|}{VOLD_{j,d,t}}, \quad (8)$$

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

Given that a stock may be included in multiple ETFs, we calculate the weighted average ETF Amihud (2002) illiquidity for each stock *i* and quarter *t*, as shown in Equation (9):

$$ILLIQ(fund)_{i,t} = \sum W_{i,j,t}\, ILLIQ(etf)_{j,t}, \quad (9)$$

where $W_{i,j,t}$ is the share weight of stock *i* in ETF *j*'s portfolio out of the total shares of all stocks in the set of ETF *j* at the end of quarter *t* and $ILLIQ(etf)_{j,t}$ is the Amihud illiquidity of ETF *j* in quarter *t*.

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 (10):

$$Liquidity\ mismatch_{i,t} = \frac{ILLIQ(stock)_{i,t}}{ILLIQ(fund)_{i,t}}. \tag{10}$$

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 for the main variables used in our baseline tests. Our sample includes 109,979 stock-quarter observations for U.S. firms over the period 2000 to 2023. Consistent with the finding of Greenwood and Thesmar (2011), stock price fragility has increased over time. The mean fragility mesure is 0.0174, with a median of 0.0057, which are similar to the values reported in Friberg, Goldstein, and Hankins (2020).[3] ETF ownership has a mean of 3.52% (3.53% using *bfm* measure) and a range of 0 to 11.59%

[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, Goldstein, and Hankins (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.

(0 to 11.60% for the *bfm* measure).[4] We also report other characteristics of our sample. The mean liquidity mismatch is 1.8557, with a median of 0.4318 and a 75th percentile of 1.2284. On average, each stock is held by 185 mutual funds per quarter. The average market value and book-to-market ratio are 3.48 million and 0.5039, respectively. The typical firm in the sample has been publicly listed for approximately 16 years.

To better illustrate liquidity mismatch, we complement our stock-level analysis by examining ETF-level statistics. While Panel A of Table 1 presents liquidity mismatch at the stock level—measured as the ratio of a stock's Amihud illiquidity to the weighted average illiquidity of the ETFs holding that stock—Panel B shifts the focus to the ETF level. This approach allows for a more direct assessment of liquidity mismatches by comparing the liquidity of ETFs with that of their underlying holdings.

Panel B of Table 1 reports liquidity mismatch statistics for the ten largest ETFs by assets under management (AUM) in Quarter 4 2023. The results show substantial mismatches: these large ETFs are significantly more liquid than their underlying stocks. For example, the largest traded ETF, the S&P 500 ETF Trust (SPY), has an average Amihud's illiquidity of 0.160, while the weighted average illiquidity of its underlying stocks over the same period is 35.813. This results in a liquidity mismatch ratio of 224.394, indicating substantial liquidity shocks to be transmitted from the ETF to the underlying stocks. These findings reinforce the idea that stocks held by highly liquidly liquid ETFs are more vulnerable to liquidity-driven trading pressure.[5]

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[4] Our average ETF ownership measure (*bfm*) is 2.45% before 2016, which is consistent with that of Ben-David, Franzoni, and Moussawi (2018), who find an average firm-level ETF ownership of 2.6% from 2000-2015.

[5] At the stock level, an analysis of the top 10 largest ETFs by held shares reveals that the median Amihud illiquidity for these ETFs is 19.254, while the average Amihud illiquidity of their underlying stocks is 275.286. This indicates that ETFs are considerably more liquid (or less illiquid) than the stocks they hold. The median liquidity mismatch is about 9.109, with 98.268% of the underlying stocks being less liquid than their holding ETFs (mismatch > 1). The liquidity mismatch is even more pronounced among the top 5 largest ETFs. This suggests that the most actively traded ETFs create heightened liquidity-driven trading pressure on their underlying stocks, which are significantly less liquid, resulting in a greater liquidity mismatch. These findings, when compared to the statistics in Table 1, further emphasize that more liquid ETFs tend to exhibit larger liquidity mismatches.

[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 of stock price fragility on ETF ownership along with control variables.[6] The regression is as follows.

$$Fragility_{i,t+1} = \alpha + \beta_1 ETF_{i,t} + \beta_2 Ln(\#Mfunds_{i,t}) + \beta_3 Ln(ME_{i,t}) + \beta_4 Volatility_{i,t}$$
$$+ \beta_5 Negative\ skewness_{i,t} + \beta_6 BTM_{i,t} + \beta_7 Firm\ age_{i,t}$$
$$+ \beta_8 Active\ fund\ ownership_{i,t} + \beta_9 Index\ fund\ ownership_{i,t} + \varepsilon_{i,t}, \quad (10)$$

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 (0.249) on *ETF (ils)* 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 remains robust. The coefficient on *ETF (ils)* is 0.049. Our results are also economically significant. The result in Column (2) indicates that a one-standard-deviation increase in ETF

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

ownership is related to an increase of 9.08% over the mean stock price fragility.[7] 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. Columns (3) and (4) replicate the baseline regressions but substitute *ETF (ils)* with *ETF (bfm)*. Results are robust and qualitatively similar.

[Insert Table 2 about here]

3.2 Identification tests

3.2.1 An instrumental variable from Russell index reconstitution

To establish a causal interpretation of the positive relation between ETF ownership and stock price fragility, we follow the identification strategy from Ben-David, Franzoni, and Moussawi. (2018) and Lin, Mei, Tan and Zhang (2024). Specifically, we exploit the variation in ETF ownership using exogenous stock reconstitution in the Russell 1000 and 2000 indexes. The Russell 1000 index comprises the largest 1000 stocks by market capitalization, while the Russell 2000 index comprises the next 2000 largest stocks. The Russell indexes are reconstituted at the end of June each year based on a stock's end-of-May market capitalization. The arbitrary index assignment has a strong impact on ETF ownership because ETFs track a stock's portfolio weight in the index (Ben-David, Franzoni, and Moussawi, 2018). For example, the 1000th stock is given a relatively smaller portfolio weight for inclusion in the Russell 1000, while the 1001st stock is given a much larger weight for inclusion in the Russell 2000. In other words, we expect higher ETF ownership for stocks with rankings just after 1000th than for stocks with rankings just before 1000th. Therefore, the changes in index membership for stocks with market capitalizations close to the cutoff (1000th) are relatively random events after we control for the assignment variable (market capitalization), which is from a random variation in stock prices at the end of May.

[7] The calculation of economic significance is as follows: 9.08%=0.049*0.0302/0.0163.

Before 2007, the index assignment followed a simple threshold rule to rank and assign the stocks according to their total market capitalization. However, starting in 2007, Russell Inc. adopted a new banding rule that allows stocks to switch from their current index to a different market-capitalization-based Russell index only if they move beyond the cumulative 5% range of the market capitalization breakpoint of the 1,000th stock. Otherwise, the stocks remain in their current index. In particular, Russell first calculates the cumulative market capitalization breakpoint for the 1,000th stock and then subtracts (adds) 2.5% from (to) the breakpoint to create the upper (lower) band. An existing member of the Russell 1000 (2000) can move to the Russell 2000 (1000) only if it passes the lower (upper) band. Since the new banding rule was introduced, switching has become less frequent, largely because the banding rule requires significant changes in market capitalization for a stock switch.

Following Coles, Heath, and Ringgenberg (2022) and Chowdhury, et al. (2024), we exploit the post-2007 Russell index reconstitution to identify the relationship between ETF ownership and stock price fragility. After controlling for the assignment variable (market capitalization), the changes in index membership for stocks with a market capitalization close to the cutoff (1,000th) are relatively random events that reflect random variation in a firm's stock price at the end of May. We adopt an instrumental variable (IV) approach and divide our sample into two sets, the treated (i.e., actual switchers) and the control (i.e., potential switchers) stocks. In the first set (the upper band), we consider the stocks in the Russell 2000 that have the potential to cross the upper band, which means they would switch to the Russell 1000 after reconstitution.

We define the instrument variable $Switchto1000_{i,t-1}$ as a dummy variable for stock *i*, which belongs to the Russell 2000 index before the index reconstitution in year *t*. $Switchto1000_{i,t-1}$ equals 1 if stock *i* switches to the Russell 1000 index after the index reconstitution in year *t*, and 0 otherwise. Similarly, we define the instrument variable

$Switchto2000_{i,t-1}$ as a dummy variable for stock *i* that belongs to the Russell 1000 index before the index reconstitution in year *t*. $Switchto2000_{i,t-1}$ equals 1 if stock *i* switches to the Russell 2000 index after the index reconstitution in year *t*, and 0 otherwise. We consider 200, 250, and 300 bandwidths on each side of the upper or lower band to take into account significant change of market capitalization to qualify switch.

To formally conduct the test, we introduce a two-stage least squared (2SLS) regression model by instrumenting ETF ownership with the instrument variable, $Switchto1000_{i,t-1}$ or $Switchto2000_{i,t-1}$, in the first stage regression and regress stock price fragility on predicted ETF ownership in the second stage regression. We also include all control variables used in the baseline regression. In the first stage, we predict ETF ownership in the following quarter with $Switchto1000_{i,t-1}$ or $Switchto2000_{i,t-1}$, including industry fixed effects (h_j) and year fixed effects (δ_t), as shown below.

$$ETF_{\ i,t} = \alpha + \beta_1 * Switched_{i,t-1} + \sum_k \beta_k Controls_{i,t-1}^{k} + h_j + \delta_t + \varepsilon_{i,t} \qquad (11)$$

In the second stage, we run Fama-Macbeth regressions of stock price fragility in the fourth quarter on predicted ETF ownership from the first stage regression along with control variables.

$$Fragility_{i,t+1} = \alpha + \beta_1 \widehat{ETF}_{i,t} + \sum_k \beta_k Controls_{i,t}^{k} + \varepsilon_{i,t} \qquad (12)$$

Table 3 reports the regression results. Panels A and B show the first- and second-stage regression results. Each panel has six columns with different bandwidths (200, 250, and 300) for both the upper (Columns (1) to (3)) and the lower bands (Columns (4) to (6)).

In Panel A, the estimated coefficients on the instrument $Switchto1000_{i,t}$ ($Switchto2000_{i,t}$) are negative (positive) for the upper (lower) band, with statistical significance at the 1% level. This outcome lends support to the instrument relevance condition. The interpretation is that when a stock switches from the Russell 2000 (1000) index to the

Russell 1000 (2000) index, its ETF ownership declines (increases) because its market capitalization is given a lower (higher) weight than when it was included in the Russell 1000 (2000) index. For instance, in Column (1), when a stock switches from Russell 2000 to Russel 1000, ETF ownership decreases by 0.3% when the bandwidth is 200. In contrast, in Column (4), when a stock switches from Russell 1000 to Russell 2000, ETF ownership increases by 0.2% when the bandwidth is 200. The opposite first-stage regression results between the upper and lower bands also strengthen our argument that our Russell reconstitution identification is a good and relevant instrument.

[Insert Table 3 about here]

Panel B presents the second-stage results, where the dependent variable is the *Fragility*. In Columns (1) to (3), the coefficients on the predicted ETF ownership are statistically significant across almost all bandwidths, with coefficients ranging from 0.066 to 0.107. Furthermore, in Columns (4) to (6), the coefficients on the predicted ETF ownership with the lower band are statistically significant across all bandwidths, with coefficients ranging from 0.047 to 0.121. Overall, our results provide causal evidence that higher ETF ownership leads to a higher stock price fragility. Panels C and D replicate 2SLS regressions by substituting *ETF (bfm)* with *ETF (ils)*. We find that all results are qualitatively consistent.

3.2.2 An exogenous shock from BlackRock's acquisition of Barclay's iShares

To further address endogeneity concerns and establish a causal interpretation of our results, we exploit BlackRock's 2009 acquisition of Barclays Global Investors (BGI) and its iShares ETF platform as an exogenous shock to ETF ownership. This acquisition provides a quasi-natural experiment enabling a difference-in-difference (DiD) test. Zou (2019) documents that following the acquisition, iShares ETFs experienced a 19% rise in ETF flows for stocks with high iShares ETF ownership compared to those with low or no iShares ETF ownership.[8] This surge in inflows was exogenous, driven by BlackRock's resources rather than the fundamentals or managerial actions of the enterprises.[9]

In our DID framework, following Antoniou, Li, Liu, Subrahmanyam, and Sun (2023), the treatment group consists of firms with iShares ETF ownership above the sample median before the acquisition, while the control group includes the remaining firms. To further address potential bias from firm characteristics, we employ a propensity score matching (PSM) approach. Using a logit model, we estimate the likelihood of treatment based on firm-level characteristics and match treated firms to control firms using one-to-one nearest neighbor matching with a 0.01 caliper. We then estimate a DID regression over a seven-year window using the following model:

$$Fragility_{i,t} = \alpha + \beta_1 Treat * Post + \sum_k \beta_k Controls_{i,t-1}^{k} + h_j + \delta_t + \varepsilon \qquad (13)$$

Here, *Post* equals one for the period 2010–2013 and zero for 2007–2009. *Treat* equals one for firms with iShares ETF ownership above the pre-acquisition median. The coefficients of *Treat* and *Post* are absorbed by industry fixed effect (h_j) and year-quarter fixed effect δ_t. Table 4 Panel A Column (1) shows the DiD regression results, with the interaction term being positive and significant at the 1% level, indicating that firms with high ETF ownership reduced their reliance on bank debt more than their counterparts. Specifically, the interpretation is that, compared with the non-treated group (low iShare ETF ownership), the treated group experienced sudden increase in ETF ownership due Blackrock's capital inject in iShare ETF after 2009, and consequently causes 8.6% higher stock price fragility. We also replicate the

[8] The data are published in BlackRock's 2010 Annual Report. For details, see: https://s24.q4cdn.com/856567660/files/doc_financials/2010/ar/2010-Annual-Report.pdf

[9] Zou (2019) demonstrates that BlackRock's powerful brand name, highly specialized employees, and stronger distribution channels place it at an advantage in drawing capital into its funds.

DiD regression by removing the PSM process to expand observation and find that the result, documented in Column (2), is qualitatively similar.

[Insert Table 4 about here]

Following Antoniou, et al. (2023), we further conduct an additional instrumental variable (IV) analysis using iShares ETF ownership as an instrument. This approach still leverages BlackRock's 2009 acquisition of Barclays Global Investors and its iShares unit as an exogenous shock, and limit sample period between 2007 and 2013 but without propensity matching procedure to achieve more observations. Our instrument, *TREAT * POST*, is exactly same as the interaction variable adopted in DiD model. Given that the acquisition of iShare ETF exogenously bring capital injection to iShare ETF funds, stocks with high iShare ETF ownership also experienced surge in ETF ownership (Zou, 2019). This satisfies the relevance condition. The exclusion restriction is also satisfied, as there is little reason to expect systematic changes in corporate policies between iShares and non-iShares companies solely due to the acquisition.

The first-stage regression of the IV model is specified as:

$$ETF_{i,t} = \alpha + \beta_1 TREAT * POST + \sum_k \beta_k Controls_{i,t-1}^k + h_j + \delta_t + \varepsilon \quad (14)$$

Here, the instrument (*iShares* × *POST*) captures the exogenous variation in ETF ownership. The model includes a comprehensive set of control variables, along with industry fixed effects (h_j) and year-quarter fixed effects (δ_t).

In the second stage, we replace the ETF ownership variable in the baseline Fama-Macbeth regression with its predicted value from the first-stage model:

$$Fragility_{i,t+1} = \alpha + \beta_1 \widehat{ETF}_{i,t} + \sum_k \beta_k Controls_{i,t}^k + \varepsilon \quad (15)$$

Table 4 Panel B presents the results. The first-stage regression, presented in Columns (1), confirms the instrument's validity, with the coefficient on *TREAT * POST* being significantly positive at the 1% level, justifying an increased ETF ownership for iShares firms after 2009.

The second-stage estimation, presented in Column (2), shows that the predicted ETF ownership coefficient (0.547) is significantly positive at the 1% level. Such 2SLS results remain qualitatively similar if we substitute *ETF (ils)* with *ETF (bfm)*. Our instrument approach reinforces the causal evidence that higher ETF ownership causes greater stock price fragility.

3.2.3 A quasi-natural experiment from the initiation of ETF ownership

Our main theoretical framework is that a liquidity demand shock to the ETF will quickly cause a liquidity demand shock to the constituent stocks. But in practice, authorized participants (AP), who act as market makers, will handle the creation/redemption of the ETF. Once there is a demand shock for the ETF (i.e. liquidity-driven trading), the APs may not immediately take action. In this case, there will be a delay in the transfer of the liquidity shock to the stocks. In addition, subsequent ETF creations and redemptions in the primary markets may also impact secondary market ETF trading.

To address the impact of the primary market activities, we notice that ETF primary market trading (i.e. gross creations and redemptions) is not as active as ETF secondary market trading. For instance, ETF's primary market trading value is, on average, 4.7% of the total trading value of the company stocks.[10] Therefore, the impact of primary market trading might be minimal.

To further address such potentially confounding factors brought from primary market activities that could correlate ETF ownership with stock price fragility, we conduct a narrow-window analysis following Bhojraj, Mohanram, and Zhang (2020). This analysis examines the four quarters before and after a firm is first included in an ETF, leveraging staggered ETF initiation dates as a quasi-natural experiment. The advantage of this quasi-natural experiment is to exclude subsequent primary market ETF creation/redemption activities and fully consider

[10] ETF trading activities in primary and secondary market can be found in ICI Investment Fact Book: https://www.ici.org/fact-book .

the delay of possible impact from the primary market activities. In addition, by comparing a firm's stock price fragility within this short window, we effectively use each firm as its own control, minimizing firm- or industry-level confounding effects. This approach also mitigates time-varying confounders, increasing our confidence that the observed changes are linked to ETF ownership.

We employ the following staggered difference-in-differences (DiD) Fama-Macbeth regression model at the firm-quarter level:

$$Fragility_{i,t} = \alpha_0 + \beta_1\, Initiation_{i,t-1} + \sum_k \beta_k Controls_{i,t-1}^{k} + \varepsilon\,, \tag{16}$$

where the dependent variable is the stock price fragility measure. The key variable, $Initiation_{i,t-1}$, equals 1 in the post-initiation period (four quarters after ETF inclusion) and 0 in the pre-initiation period. Control variables are consistent with the baseline model, excluding those that significantly reduce sample size. The coefficient β_1 captures the DiD effect of ETF initiation on stock price fragility.

Table 5 presents the results for 3,552 unique ETF initiations and 19,185 firm-quarter observations. In Column (1), the initiation coefficient is positive and significant at the 1% level, indicating that stock price fragility is 1.80% higher, on average, in the four quarters after ETF inclusion compared to the four quarters prior.

[Insert Table 5 about here]

To address concerns about time-variant imbalances, such as changes in ETF market maturity since their introduction in the late 1990s, we conduct a robustness check by excluding the years 2000 and 2001.[11] For the remaining 2,165 unique ETF initiations and 10,758 firm-quarter observations, the staggered DiD analysis confirms the main findings. Column (2) of Table 5 shows a similar positive effect, with stock price fragility increasing by 1.70% after

[11] In our sample, untabulated summary statistics reveal that 1,387 ETF initiations occurred in 2000 and 2001, representing 39.05% of all initiations, while those in other years are evenly distributed, averaging 2.74%.

ETF initiation. The magnitude of these results aligns with those in the full sample analysis, reinforcing the conclusion that ETF ownership causally increases stock price fragility.

3.3 Cross-sectional: Liquidity mismatch between stocks and ETFs

Importantly, we 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 (10) by adding interaction terms (*ETF*Liquidity mismatch indicator*) and the liquidity mismatch indicators. The regression is as follows:

$$Fragility_{i,t} = \beta_1 ETF_{i,t} + \beta_2 ETF_{i,t} * Liquidity\ mismatch\ indicator_{i,t}$$
$$+\beta_3 Liquidity\ mismatch\ indicator_{i,t} + \sum_k \beta_k Controls_{i,t}^k + \varepsilon_{i,t}\ . \quad (17)$$

Table 6 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) of Panel A, using *High mismatch* as the liquidity indicator, we find that the coefficient of the interaction term (*ETF (ils) * High mismatch*) is 0.098, which is statistically significant 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 (ils) * Mismatch>1*) is 0.102, which is also statistically significant at the 1% level. This finding suggests that ETF ownership increases stock price fragility, especially among stocks that are more illiquid than their ETF baskets. In Panel B, we substitute *ETF (ils)* with *ETF (bfm)* and we find that the results are qualitatively similar to the ones in Panel A. Taken together, the results from Table 6 support our argument that by being included in liquid ETF baskets, a stock is exposed to greater non-fundamental liquidity demand, especially when the stock is more illiquid.

[Insert Table 6 about here]

3.4 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[12]; 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.

[Insert Table 7 about here]

[12] Sherrill, Shirley, and Stark (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, Mohanram, and Zhang (2020) find that sector ETFs can improve stock-level information efficiency while broad ETFs cannot.

In Panel A of Table 7, we report both fund-level illiquidity statistics for broad vs. sector ETF and stock-level summary statistics on broad and sector ETF ownership. At the fund-quarter level, we find that broad ETFs are significantly more liquid and larger than sector ETFs. On average, the Amihud illiquidity of broad ETFs is 1.4063, while the Amihud illiquidity of sector ETFs is 1.7096. Our sample includes 97,458 quarterly stock-level observations for the period 2000 to 2023. The average broad ETF ownership is 2.85%, while the average sector ETF ownership is 0.41%.

At firm-quarter (stock) level, we consider 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. If our prediction is correct, we should observe that stocks included in broad ETFs, which are more liquid than sector ETFs, are more likely to be exposed to liquidity-driven trades, thereby becoming more fragile. To test this prediction, we repeat the regression in Equation (9) to investigate whether the positive association between ETF ownership and stock price fragility is driven by a certain type of ETF ownership (broad vs. sector) at firm-quarter level. 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 7 Panels B and C, where they use different ETF ownership measures (Israeli, Lee, and Sridharan, 2017 & Ben-David, Franzoni, and Moussawi, 2018)

In Panel B Column (1), we find that the coefficient (0.171) on broad ETF ownership – *Broad ETF (ils)* is positive and statistically significant at the 1% level, while the coefficient (0.047) on sector ETF ownership – *Sector ETF (ils)* is statistically insignificant. Panel C Column (1) shows qualitative similar results, where the coefficient on *Broad ETF (bfm)* is 0.146 and significant at 1% level while the coefficient on *Sector ETF (bfm)* is insignificant. Economically, a one-standard-deviation increase in broad ETF ownership is positively related to a significant increase of 28.61% over the mean stock price fragility[13], while a one-standard-deviation increase in sector ETF ownership is related to a slight decrease of 5.36% from the mean stock price fragility[14]. Both panels verify our conjecture that broad ETF ownership, instead of sector ETF ownership, is the main driver of stock price fragility.

In Columns (2) and (3) of Panels B and C, 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) of both panels, the key variables of interest are the interaction terms *Broad ETF (ils or bfm) * High mismatch (broad)* and *Sector ETF * High mismatch (sector)*. We find that the coefficient on *Broad ETF (ils or bfm) * High mismatch (broad)* is positively significant at 1% level, while the coefficient on *Sector ETF (ils or bfm) * High mismatch (sector)* is insignificant. Likewise, in Column (3) of both panels, we find that the coefficient on *Broad ETF (ils or bfm) * Mismatch>1(broad)* is positively significant at the 5% level, while the coefficient on *Sector ETF (ils or bfm) * Mismatch>1(sector)* is insignificant.

Overall, these results show that stocks with greater broad ETF ownership are more fragile, especially when the stocks are relatively less liquid compared to the ETFs, confirming our expectation that stocks included in more liquid ETFs are more likely to be exposed to liquidity-driven trades.

3.5 Cross-sectional: Covid-19 shock on liquidity-driven trading on ETF

High-quality liquid assets typically experience net buying pressures during financial crises, a phenomenon often referred to as a “flight to liquidity” (Longstaff, 2004). However, the COVID-19 crisis deviated from this pattern, exhibiting a “reverse flight to liquidity” where high-quality liquid assets faced unusual net selling pressures (Ma, Xiao, and Zeng, 2022). This reversal was largely due to significant investor outflows from mutual funds, which were

[13] The calculations of economic significance are as follows: 28.61%=0.146*0.0390/0.0199.
[14] The calculations of economic significance are as follows: -5.36%=-0.123*0.0073/0.0199.

influenced by their role in liquidity transformation. To meet redemption demands, mutual funds adhered to a pecking order, prioritizing the sale of their most liquid assets. Such behavior resulted in significant selling pressure in liquid asset markets, amplifying liquidity-driven trading activity during the crisis. ETFs, known for their liquidity, were particularly vulnerable, often being sold first, exacerbating price pressure on individual stocks under their management and increasing stock price fragility.

This phenomenon aligns with findings from Khomyn, Putniņš, and Zoican (2024) that more liquid ETFs tend to attract short-horizon, liquidity-sensitive investors. During the COVID-19 crisis, these investors were more likely to engage in liquidity-driven trading, intensifying price pressure on individual stocks held by ETFs. The heightened trading activity, coupled with market stress, contributed to stock price fragility during this period. Consequently, we hypothesize that the association between ETF ownership and stock price fragility became more pronounced during the COVID-19 shock, driven by the amplified liquidity-driven trading and price pressure on individual stocks managed by ETFs.

To test this conjecture, we interact ETF ownership with a COVID-19 dummy variable, where the dummy equals one for the period between 2020 Q1 and 2022 Q4, and zero otherwise. Using Fama-Macbeth regressions and maintaining other settings consistent with the baseline model, we examine the differential impact of ETF ownership on stock price fragility with and without the COVID-19 impact. Table 8 presents the results, showing a positive and significant coefficient for the interaction variable. For example, Column (1) indicates that the association between ETF ownership and stock price fragility was 0.60% higher during the COVID-19 period compared to the non-COVID period. In Column (2), we replace the *ETF (bfm)* measure with the *ETF (ils)* measure, finding consistent results. These findings provide robust evidence that liquidity-driven trading played a pivotal role in driving price pressure and fragility in individual stocks under ETF management during the COVID-19 crisis.

[Insert Table 8 about here]

3.6 Channel tests: mutual fund outflows

In the previous section, we argue 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 would provide a clearer and more observable measure to capture their liquidity needs based on investor outflows. Thus, 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:

$$Change\ in\ ETF\ holdings_{k,t}$$
$$= \beta_1 Outflow\ indicator_{k,t} + \beta_2 Fund\ size_{k,t} + \beta_3 ETF\ holding_{k,t-1} + \delta_t + \mu_k + \varepsilon_{k,t}, \quad (18)$$

where $Change\ in\ ETF\ holdings_{k,t}$ is calculated as the difference in the percentage of 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 9 shows the regression results of the change in ETF holdings and mutual fund outflow indicators. In Column (1), the coefficient (-0.012) on *Outflow* is negative at the 1% significance level, suggesting that mutual funds tend to reduce their holdings in ETFs when they experience outflows. In Column (2), the coefficient (-0.007) on *Large outflow* is negative at the 1% significance level, suggesting that mutual funds tend to reduce their holdings in ETFs, particularly when they experience large outflows. In Column (3), the coefficient (-0.101) 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 across the columns, the coefficient in Column (3) is not only more negative but also accompanied by a larger t-statistic, highlighting a stronger response under conditions of ample ETF liquidity. These results support our hypothesis that mutual funds actively use ETFs as a liquidity management tool, prioritizing ETF sales during outflows, especially when ETF holdings are large enough to offset redemption needs.

[Insert Table 9 about here]

4. Conclusion

The total assets under management of ETFs have grown rapidly in recent decades; thus, ETFs play an important role in shaping the financial market dynamics and stability. Our study examines how ETF ownership affects stock price fragility, emphasizing the role of liquity mismatches between ETFs and their underlying stocks. In particular, we document a positive association between ETF ownership and stock price fragility, suggesting that investors tend to use ETFs for liquidity management. As a result, liquidity-driven trades of ETFs increase the underlying stocks' exposure to non-fundamental demand shocks. To establish causality, we employ an instrumental variable from Russell index reconstitution, and exogenous shocks from the acquisition of iShare ETF and ETF initiations. We further show that the positive association is more pronounced in relatively illiquid stocks, reinforcing 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 a higher liquidity mismatch; however, we observe no significant effects for sector ETFs. In our channel tests, we show that mutual funds tend to reduce their ETF holdings primarily when they have enough ETF holdings to fully offset the scale of the fund outflow, suggesting that ETFs are used as a strategic liquidity management tool. Additionally, we use COVID-19 as a shock to liquidity-driven trading and show that the effect on stock price fragility is more pronounced during the pandemic period, highlighting how systemic liquidity shocks amplify this mechanism. Overall, these findings support our argument that ETFs can propagate non-fundamental liquidity demand to the underlying stocks through the liquidity mismatch channel.

Our study makes three significant contributions to the literature on ETFs. First, it broadens the understanding of ETF impacts by shifting the focus from the well-explored role of ETFs in information efficiency to the less-studied issue of liquidity mismatch. It demonstrates how ETF ownership can increase stock price fragility by transmitting liquidity-driven price pressure from ETFs to their underlying stocks. Second, it introduces the investor liquidity management channel as an alternative to the arbitrage channel, explaining how ETF trading propagates non-fundamental demand shocks. Our results reveal that ETFs' high liquidity—designed to meet investors' liquidity needs—can render stocks with higher ETF ownership more susceptible to such shocks. Finally, it offers new insights into how mutual funds utilize ETFs, particularly during periods of outflows. Unlike previous studies that have focused on ETF usage during inflows, this research finds that mutual funds often reduce their ETF positions to manage liquidity during outflows, providing more precise evidence of liquidity management practices.

Given that 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 impact financial market stability and how different investor types can use ETFs to achieve distinct objectives.

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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 (*ils*)	Following Israeli, Lee, and Sridharan (2017), we calculate ETF ownership as the percentage of firm's common shares outstanding held by ETFs at the end of each quarter.	Thomson Reuters, CRSP
ETF (*bfm*)	Following Ben-David, Franzoni and Moussawi (2018), we calculate ETF ownership 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, Mohanram, and Zhang (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", "w*ils*hire", "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:	CRSP

	$$r_{i,t} = \alpha_i + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \varepsilon_{i,t}$$ 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*.	
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

Panel A provides descriptive statistics for the variables in our quarterly sample of large U.S. publicly traded firms from 2000 to 2023. The table presents the means, standard deviations, and different percentiles (such as 25th, 50th, and 75th) for all variables used in the analysis of ETF ownership, liquidity mismatch, and fragility. It reports descriptive statistics for the overall sample. 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 the 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 1st and 99th percentiles. All variable definitions are provided in Appendix A. Panel B presents summary statistics on liquidity mismatch at the ETF level for the top 10 ETFs by assets under management (AUM). ETFs are ranked from largest to smallest based on market size, calculated as the product of the ETF's trading price and trading volume. This panel reports Amihud illiquidity statistics for ETFs and the weighted average Amihud illiquidity statistics for their underlying stocks. The last column presents liquidity mismatch, defined as the ratio of Amihud illiquidity for underlying stocks to that of the ETF.

Panel A: Summary statistics

	N=109,979 (firm-quarters)						
Variable	Mean	SD	P1	P25	Median	P75	P99
Fragility	0.0163	0.0418	0.0000	0.0019	0.0057	0.0156	0.1829
ETF (*ils*)	0.0352	0.0302	0.0000	0.0082	0.0288	0.0556	0.1159
ETF (*bfm*)	0.0353	0.0308	0.0000	0.0092	0.0276	0.0551	0.1160
Liquidity mismatch	1.8557	6.0087	0.0055	0.1581	0.4318	1.2284	30.1549
Ln(#Mfunds)	5.2177	0.7774	2.7081	4.7958	5.2832	5.7398	6.7417
Ln(ME)	1.4993	1.2927	-0.6818	0.5023	1.2665	2.3187	5.1802
Volatility	0.0215	0.0119	0.0072	0.0134	0.0183	0.0258	0.0714
Negative skewness	-0.1446	1.3422	-3.0132	-1.1941	-0.2037	0.8924	2.9181
Book-to-market	0.5039	0.3545	-0.1486	0.2586	0.4425	0.6766	1.8453
Firm age	2.8057	0.9438	0.0000	2.1972	2.9444	3.6109	4.0943
Active fund ownership	0.1971	0.1005	0.0000	0.1273	0.1945	0.2627	0.4424
Index fund ownership	0.0260	0.0196	0.0000	0.0122	0.0236	0.0361	0.0870

Panel B: Liquidity mismatch for the top 10 ETF funds

ETF fund name	Ticker	AUM ($ bil)	ETF market size ($ bil)	ETF trading volume (mil)	Amihud Illiquidity (stock)	Amihud Illiquidity (ETF)	Liquidity mismatch
SPDR S&P 500 ETF Trust	SPY	496.971	26.500	55.762	35.813	0.160	224.394
iShares Trust: iShares Russell 2000 ETF	IWM	74.081	2.480	13.847	615.302	1.507	408.349
Vanguard Index Funds: Vanguard 500 Index Fund; ETF Shares	VFFSX	979.392	1.870	4.271	26.929	3.038	8.865
iShares Trust: iShares Core S&P 500 ETF	IVV	401.317	1.830	4.063	19.129	2.842	6.731
Vanguard Index Funds: Vanguard Value Index Fund; ETF Shares	VTV	155.753	0.451	3.021	39.042	16.502	2.366
iShares Trust: iShares Russell 1000 Value ETF	IWD	55.210	0.382	2.611	104.783	17.222	6.084
iShares Trust: iShares Core S&P Mid-Cap ETF	IJH	76.420	0.342	1.230	238.916	24.244	9.855
iShares Trust: iShares Russell 1000 Growth ETF	IWF	81.815	0.292	1.063	55.545	21.286	2.609
Vanguard Index Funds: Vanguard Small-Cap Index Fund; ETF Shares	VSMAX	135.455	0.215	1.022	1397.150	71.113	19.647
Vanguard Index Funds: Vanguard Mid-Cap Index Fund; ETF Shares	VMCIX	155.631	0.124	0.602	89.724	55.753	1.609

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 2000-2023 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.

VARIABLES	(1) Fragility	(2) Fragility	(3) Fragility	(4) Fragility
ETF (ils)	0.249***	0.049***		
	(9.16)	(3.09)		
ETF (bfm)			0.193***	0.046*
			(5.82)	(1.70)
Ln(#Mfunds)		-0.012***		-0.012***
		(-13.44)		(-13.37)
Ln(ME)		0.003***		0.003***
		(12.19)		(11.96)
Volatility		-0.047*		-0.048*
		(-1.83)		(-1.86)
Negative skewness		0.000		0.000
		(0.82)		(0.87)
Book-to-market		-0.005***		-0.005***
		(-8.29)		(-8.30)
Firm age		-0.000		0.000
		(-0.09)		(0.45)
Active fund ownership		0.155***		0.155***
		(23.26)		(23.21)
Index fund ownership		0.296***		0.301***
		(7.84)		(7.95)
Observations	109,979	109,979	109,979	109,979
Adjusted R-squared	0.012	0.221	0.007	0.221
Number of groups	91	91	91	91
Fama-Macbeth	Y	Y	Y	Y

Table 3. An instrumental variable from Russell index reconstitution

This table reports the regression results from the instrumental variable estimation using the reconstitution of the Russell 1000 and Russell 2000 indexes. Our sample covers firm-year observations from 2000 to 2021. Panel A shows the first- and Panel B the second-stage results. Columns (1) to (3) and (4) to (6) present bandwidths that range from 200 to 300 stocks around the upper and lower bands, respectively. In Panel A, the dependent variable ETF ownership (*ils*) in the third quarter. The instrumental variables are *Switchto1000* and *Switchto2000*, which are categorical variables. *Switchto1000* equals 1 if a stock moves from the Russell 2000 to the Russell 1000 index after reconstitution, and 0 otherwise. Similarly, *Switch2000*, equals 1 if a stock moves from the Russell 1000 to the Russell 2000 index, and 0 otherwise. In Panel B, the second-stage results use stock price fragility (*Fragility*) as the dependent variable, which captures stock-level exposure to non-fundamental demand shocks calculated using mutual fund ownership and flow variance-covariance. The main explanatory variable is the instrumented ETF ownership, denoted by $\widehat{ETF_{(\iota ls)}}$. The control variables used in all panels are the same as those presented in Table 2. Panels C and D replicate the analysis using ETF (*bfm*) measure. 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.

Panel A: First stage regression using ETF (*ils*)

	(1)	(2)	(3)	(4)	(5)	(6)
		Upper band			Lower band	
	Band200	Band250	Band300	Band200	Band250	Band300
VARIABLES	ETF (*ils*)	ETF (*ils*)	ETF (*ils*)	ETF (*ils*)	ETF (*ils*)	ETF (*ils*)
Switchto1000	-0.003***	-0.003***	-0.002***			
	(-5.44)	(-5.96)	(-6.01)			
Switchto2000				0.002**	0.003***	0.003***
				(2.43)	(3.32)	(3.72)
Ln(#Mfunds)	0.008***	0.007***	0.007***	0.008***	0.007***	0.007***
	(7.28)	(6.89)	(6.77)	(7.25)	(6.87)	(6.72)
Ln(ME)	-0.008***	-0.009***	-0.010***	-0.008***	-0.009***	-0.010***
	(-10.17)	(-12.53)	(-14.96)	(-10.13)	(-12.60)	(-15.09)
Volatility	-0.024	-0.031	-0.039*	-0.026	-0.033	-0.042*
	(-0.89)	(-1.24)	(-1.71)	(-0.97)	(-1.34)	(-1.85)
Negative skewness	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.14)	(-0.34)	(-1.16)	(-0.23)	(-0.45)	(-1.27)
Book-to-market	-0.004***	-0.003***	-0.003***	-0.004***	-0.003***	-0.003***
	(-3.68)	(-3.66)	(-3.56)	(-3.68)	(-3.67)	(-3.57)
Firm age	0.004***	0.004***	0.005***	0.004***	0.004***	0.005***
	(9.83)	(10.94)	(11.60)	(9.80)	(10.91)	(11.58)
Active fund ownership	0.014***	0.015***	0.015***	0.013***	0.015***	0.015***
	(3.63)	(4.30)	(4.46)	(3.58)	(4.24)	(4.40)
Index fund ownership	0.474***	0.475***	0.479***	0.475***	0.477***	0.481***
	(16.89)	(18.37)	(19.42)	(16.89)	(18.38)	(19.45)
Observations	19,029	23,947	28,899	19,029	23,947	28,899
Adjusted R-squared	0.809	0.811	0.809	0.809	0.811	0.809
Industry FE	Y	Y	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y	Y	Y

Panel B: Second stage regression using ETF (*ils*)

	(1)	(2)	(3)	(4)	(5)	(6)
		Upper band			Lower band	
	Band200	Band250	Band300	Band200	Band250	Band300
VARIABLES	ETF	ETF	ETF	ETF	ETF	ETF
$\widehat{ETF\ (\iota ls)}$	0.107***	0.066*	0.030	0.121***	0.082**	0.047*
	(2.70)	(1.97)	(0.96)	(2.96)	(2.37)	(1.65)
Ln(#Mfunds)	-0.035***	-0.031***	-0.030***	-0.035***	-0.031***	-0.030***
	(-12.74)	(-14.16)	(-15.03)	(-12.71)	(-14.09)	(-14.95)
Ln(ME)	0.008***	0.006***	0.007***	0.008***	0.006***	0.007***

	(3.95)	(4.02)	(4.89)	(3.96)	(4.05)	(4.91)
Volatility	-0.067	-0.052	-0.053	-0.063	-0.048	-0.049
	(-1.05)	(-1.00)	(-1.20)	(-0.99)	(-0.94)	(-1.13)
Negative skewness	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.29)	(-0.05)	(-0.18)	(-0.29)	(-0.05)	(-0.20)
Book-to-market	-0.008***	-0.009***	-0.008***	-0.008***	-0.009***	-0.008***
	(-7.56)	(-9.65)	(-9.66)	(-7.55)	(-9.66)	(-9.69)
Firm age	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(3.79)	(4.34)	(4.17)	(3.55)	(4.13)	(3.83)
Active fund ownership	0.237***	0.215***	0.210***	0.237***	0.215***	0.210***
	(18.44)	(20.47)	(21.27)	(18.43)	(20.45)	(21.26)
Index fund ownership	0.691***	0.605***	0.623***	0.682***	0.596***	0.614***
	(6.49)	(7.31)	(8.44)	(6.45)	(7.28)	(8.45)
Observations	19,029	23,947	28,899	19,029	23,947	28,899
Adjusted R-squared	0.238	0.220	0.211	0.238	0.220	0.211
Number of groups	84	84	84	84	84	84
Fama-Macbeth	Y	Y	Y	Y	Y	Y

Panel C: First stage regression using ETF (*bfm*)

	(1)	(2)	(3)	(4)	(5)	(6)
	Upper band			Lower band		
	Band200	Band250	Band300	Band200	Band250	Band300
VARIABLES	ETF (*bfm*)	ETF (*bfm*)	ETF (*bfm*)	ETF (*bfm*)	ETF (*bfm*)	ETF (*bfm*)
Switchto1000	-0.003***	-0.003***	-0.003***			
	(-5.40)	(-5.94)	(-6.47)			
Switchto2000				0.002*	0.003***	0.003***
				(1.78)	(2.94)	(3.38)
Observations	19,029	23,947	28,899	19,029	23,947	28,899
Adjusted R-squared	0.773	0.774	0.777	0.773	0.774	0.777
Industry FE	Y	Y	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y	Y	Y
Controls in Panel A	Y	Y	Y	Y	Y	Y

Panel D: Second stage regression using ETF (*bfm*)

	(1)	(2)	(3)	(4)	(5)	(6)
	Upper band			Lower band		
	Band200	Band250	Band300	Band200	Band250	Band300
VARIABLES	ETF	ETF	ETF	ETF	ETF	ETF
ETF (bfm)	0.081**	0.053*	0.027	0.094**	0.067**	0.043*
	(2.30)	(1.77)	(1.01)	(2.60)	(2.22)	(1.69)
Observations	19,029	23,947	28,899	19,029	23,947	28,899
Adjusted R-squared	0.237	0.219	0.211	0.237	0.219	0.210
Number of groups	84	84	84	84	84	84
Fama-Macbeth	Y	Y	Y	Y	Y	Y
Controls in Panel B	Y	Y	Y	Y	Y	Y

Table 4. An exogenous shock from BlackRock's acquisition of Barclay's iShares

This table presents the quasi-natural experiment results. Our sample covers the 2007-2013 period around the exogenous shock in 2009. Panel A shows DiD regression results. 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. The main variable of interest, *TREAT*POST*, is an interaction variable capturing the difference in difference effect. *TREAT* is a dummy variable that equals one if the stock has above-the-median iShare ownership prior to the shock, and zero otherwise. *POST* is a dummy variable that equals one if the time is later than the 2009 exogenous shock year, and zero otherwise. Panel B shows 2SLS regression results, where the instrumental variable is *TREAT*POST*. The first stage regression shows the association between the instrumental variable and ETF ownership, while the second stage shows the association between the predicted ETF ownership and stock price fragility. 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.

Panel A: DiD model

VARIABLES	(1) Fragility	(2) Fragility
Treat * Post	0.086**	0.083***
	(2.006)	(3.428)
Observations	1,316	24,087
Adjusted R-squared	0.495	0.444
Controls	Y	Y
PS matched	Y	N
Industry FE	Y	Y
Year-quarter FE	Y	Y

Panel B: 2SLS model

VARIABLES	(1) ETF (*ils*) 1st stage	(2) Fragility 2nd stage	(3) ETF (*bfm*) 1st stage	(4) Fragility 2nd stage
*Treat * Post*	0.007***		0.007***	
	(4.57)		(4.43)	
$\widehat{ETF\ (ils)}$		0.547***		
		(3.16)		
$\widehat{ETF\ (bfm)}$				0.500***
				(3.16)
Observations	24,087	24,087	24,087	24,087
R-squared	0.640	0.165	0.616	0.165
Number of groups	N/A	28	N/A	28
Controls	Y	Y	Y	Y
Fama-Macbeth	N	Y	N	Y

Table 5. A quasi-natural experiment from the initiation of ETF ownership

This table presents the estimated coefficients from Fama-Macbeth regressions explaining the association between staggered initiation of ETF ownership and stock price fragility, along with other control variables. Our initial sample covers the 2000-2023 period. Column (1) limits the sample to four quarters before and after ETF initiation, while Column (2) excludes ETF initiation between 2000 and 2002. 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. The main variable of interest, *Initiation*, is a dummy variable that equals one (the four quarters after the initiation of ETF ownership) and zero (the four quarters before the initiation of ETF ownership). 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.

VARIABLES	(1) Fragility	(2) Fragility
Initiation	0.018***	0.017***
	(5.74)	(5.18)
Ln(#Mfunds)	-0.013***	-0.007***
	(-4.52)	(-4.67)
Ln(ME)	0.002***	0.001
	(2.92)	(1.61)
Volatility	-0.046	-0.069
	(-0.59)	(-0.81)
Negative skewness	0.001	0.001
	(1.31)	(1.30)
Book-to-market	-0.004***	-0.003*
	(-2.64)	(-1.90)
Firm age	0.001***	0.001***
	(3.07)	(2.70)
Active fund ownership	0.155***	0.130***
	(9.27)	(11.00)
Index fund ownership	0.308***	0.098
	(2.82)	(1.42)
Observations	19,185	10,758
R-squared	0.274	0.292
Number of groups	95	87
Fama-Macbeth	Y	Y

Table 6. 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. Panel A uses *ETF (ils)* to proxy for ETF ownership, while Panel B uses *ETF (bfm)* to proxy for ETF ownership. We report Fama-MacBeth estimates, which are equally weighted quarter by quarter. Our sample covers the 2000-2023 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 the 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.

Panel A: Cross-sectional tests using ETF (*ils*)

VARIABLES	(1) Fragility	(2) Fragility
ETF (*ils*) * High mismatch	0.100**	
	(2.60)	
ETF (*ils*) * Mismatch > 1		0.287**
		(2.33)
High mismatch	0.000	
	(0.54)	
Mismatch > 1		0.001
		(1.57)
ETF (*ils*)	-0.029	0.010
	(-1.00)	(0.84)
Observations	109,979	109,979
Adjusted R-squared	0.223	0.223
Number of groups	91	91
Fama-Macbeth	Y	Y
Controls	Y	Y

Panel B: Cross-sectional tests using ETF (*bfm*)

VARIABLES	(1) Fragility	(2) Fragility
ETF (*bfm*) * High mismatch	0.077**	
	(2.09)	
ETF (*bfm*) * Mismatch > 1		0.252**
		(1.99)
High mismatch	0.001	
	(1.37)	
Mismatch > 1		0.001**
		(2.24)
ETF (*bfm*)	-0.017	0.010
	(-0.59)	(0.62)
Observations	109,979	109,979
Adjusted R-squared	0.223	0.223
Number of groups	91	91
Fama-Macbeth	Y	Y
Controls	Y	Y

Table 7. 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. Panel A reports the descriptive statistics at fund- and firm- level for broad vs. sector ETF. Panels B and C shows cross-sectional tests using different ETF measures. We report Fama-MacBeth estimates, which are equal weighted quarter by quarter, and t-statistics in parentheses. Our sample covers the 2000-2023 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.

Panel A: Descriptive statistics at fund- and firm- level for broad vs. sector ETF

N=50,636 (ETF fund - quarter level)						
	Broad ETF (26,062 ETF-quarter observations)		Sector ETF (24,574 ETF-quarter observations)			
Variable	Mean	SD	Mean	SD	Difference	T-statistics
Illiquidity	1.4063	0.0488	1.7096	0.0546	-0.3033***	(-4.1524)

N=97,458 (firm-quarters)							
Variable	Mean	SD	P1	P25	Median	P75	P99
Fragility	0.0199	0.1006	0.0000	0.0016	0.0059	0.0173	0.2131
Broad ETF (*ils*)	0.0555	0.0640	0.0001	0.0111	0.0272	0.0885	0.2472
Sector ETF (*ils*)	0.0039	0.0087	0.0000	0.0002	0.0007	0.0042	0.0338
Broad ETF (*bfm*)	0.0545	0.0621	0.0001	0.0106	0.0253	0.0892	0.2399
Sector ETF (*bfm*)	0.0040	0.0070	0.0000	0.0002	0.0008	0.0045	0.0367

Panel B: Cross-sectional tests using ETF (*ils*) (firm-quarter level)

VARIABLES	(1) Fragility	(2) Fragility	(3) Fragility
Broad ETF (*ils*)	0.171***	0.040	0.110***
	(2.79)	(0.91)	(3.24)
Sector ETF (*ils*)	0.047	0.164	-0.004
	(0.38)	(0.54)	(-0.04)
Broad ETF (*ils*) * High mismatch (broad)		0.178***	
		(3.40)	
Sector ETF (*ils*) * High mismatch (sector)		-0.418	
		(-1.19)	
High mismatch (broad)		-0.000	
		(-0.34)	
High mismatch (sector)		0.002***	
		(6.07)	
Broad ETF (*ils*) * Mismatch>1 (broad)			0.230**
			(1.99)
Sector ETF (*ils*) * Mismatch>1 (sector)			0.694
			(0.74)
Mismatch>1 (broad)			0.001*
			(1.72)
Mismatch>1 (sector)			0.002***
			(4.18)
Observations	97,458	97,458	97,458
R-squared	0.432	0.440	0.440
Number of groups	92	92	92
Controls	Y	Y	Y
Fama-Macbeth	Y	Y	Y

Panel C: Cross-sectional tests using ETF (*bfm*) (firm-quarter level)

VARIABLES	(1) Fragility	(2) Fragility	(3) Fragility
Broad ETF (*bfm*)	0.146**	0.039	0.096***
	(2.22)	(0.89)	(2.78)
Sector ETF (*bfm*)	-0.123	-0.126	-0.159*
	(-1.54)	(-0.97)	(-1.78)
Broad ETF (*bfm*) * High mismatch (broad)		0.154***	
		(3.07)	
Sector ETF (*bfm*) * High mismatch (sector)		-0.182	
		(-1.15)	
High mismatch (broad)		0.000	
		(1.13)	
High mismatch (sector)		0.002***	
		(6.96)	
Broad ETF (*bfm*) * Mismatch>1 (broad)			0.148*
			(1.71)
Sector ETF (*bfm*) * Mismatch>1 (sector)			0.853
			(0.90)
Mismatch>1 (broad)			0.001***
			(2.65)
Mismatch>1 (sector)			0.002***
			(3.91)
Observations	97,458	97,458	97,458
R-squared	0.430	0.437	0.437
Number of groups	92	92	92
Controls	Y	Y	Y
Fama-Macbeth	Y	Y	Y

Table 8. Heterogeneity tests: Covid-19 shock

This table presents the estimated coefficients from Fama-Macbeth regressions explaining the effect of COVID-19 shock on stock price fragility. Our sample covers the 2000-2023 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. The main variable of interest is the interaction between the COVID-19 dummy variable and ETF ownership (Covid * ETF). The control variables used in all panels are the same as those presented in Table 2. 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.

VARIABLES	(1) Fragility	(2) Fragility
Covid * ETF (*ils*)	0.006***	
	(3.31)	
ETF (*ils*)	0.501**	
	(2.01)	
Covid * ETF (*bfm*)		0.006***
		(3.31)
ETF (*bfm*)		0.462
		(1.64)
Observations	109,979	109,979
R-squared	0.202	0.202
Number of groups	91	91
Fama-Macbeth	Y	Y
Controls	Y	Y

Table 9. 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 2000-2023 period and 2,035 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 holdings 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 percentage of fund's outflow is less than its percentage of 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 of 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.

VARIABLES	(1) Change in ETF holding (%)	(2) Change in ETF holding (%)	(3) Change in ETF holding (%)
Outflow	-0.012***		
	(-5.97)		
Large outflow		-0.007***	
		(-3.78)	
Outflow < ETF			-0.101***
			(-8.22)
Fund size	0.009***	0.009***	0.008***
	(7.97)	(7.94)	(7.38)
Lag ETF holding	-0.000***	-0.000***	-0.000***
	(-38.08)	(-38.06)	(-35.55)
Observations	94,170	94,170	94,170
Number of funds	2,035	2,035	2,035
Adjusted R-squared	0.086	0.085	0.089
Fund F.E.	Y	Y	Y
Year-quarter F.E.	Y	Y	Y