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# Exchange traded funds and asset return correlations

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## Abstract

We provide novel evidence supporting the notion that arbitrageurs can contribute to return comovement via exchange trade funds (ETF) arbitrage. Using a large sample of US equity ETF holdings, we document the link between measures of ETF activity and return comovement at both the fund and the stock levels, after controlling for a host of variables and fixed effects and by exploiting the 'discontinuity' between stock indices. The effect is also stronger among small and illiquid stocks. An examination of ETF return autocorrelations and stock lagged beta provides evidence for price reversal, suggesting that some ETF-driven return comovement may be excessive.

**KEYWORDS**

exchange-traded-fund, correlation, arbitrage

**JEL CLASSIFICATION**

G23, G12

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# 1 | INTRODUCTION

Perhaps due to a half-century of encouragement from finance academics, investment assets are increasingly indexed, but the implications for asset prices of large amounts of indexed investment are not well understood. Citing evidence of mispricing and increased correlations among asset returns, Wurgler (2010) warns that over-indexing may result in contagion and mispricing risk. Exchange-traded funds (ETFs), baskets of equities traded on an exchange like stocks, are a growing asset class that has made indexing cheaper and more convenient for many investors. US-based exchange-traded funds had US $ 1.7 trillion in assets under management by the end of 2013.[1] Since these funds will by all measures play a large role in the future of saving and investing, it is important to understand if and how they will affect prices, both in absolute and compared to traditional mutual funds and institutions.

Along with information, ETFs have a potential to transmit non-fundamental shocks. Demand for ETFs results in price pressure, which is then transmitted to the underlying basket of shares as arbitrageurs simultaneously take opposite positions in the ETF and the underlying shares.[2] As a result, stocks held by ETFs might comove more with each other than warranted by common exposure to fundamentals. Arbitrageurs, who are generally enforcers of price efficiency, can thus at times contribute to excess comovement, consistent with the results in Shleifer & Vishny (1997), Hong, Kubik, & Fishman (2012) and Lou & Polk (2013). While correlated trading of stocks in the same sector or style category may also create non-fundamental shocks, to the extent that investors have some discretion in deciding when and what to trade, ETF arbitrage is more likely than other types of correlated order flow in driving return comovement among its component stocks.

A large literature on stock comovement has found that adding a stock to an index affects its price (Harris & Gurel, 1986; Kaul, Mehrotra, & Morck, 2002; Lynch & Mendenhall, 1997; Shleifer, 1986; Wurgler and Zhuravskaya, 2002) and correlation between the newly added stocks and other stocks in the index increases (Barberis et al., 2005; Goetzmann & Massa, 2003 for the S&P 500; and Greenwood & Sosner, 2007 for the Nikkei 225). This literature is subject to the caveat that missing fundamental factors are driving both the index addition and deletion decision and comovement.[3] Examining arbitrage-driven ETF turnover helps to alleviate this concern since the relative mispricing between ETF and its underlying stocks is not directly related to index addition and deletion decision. Throughout our empirical analysis, we do control for other forms of index trading in order to isolate the incremental impact of ETF arbitrage on return comovement.

Using a large panel of 549 US equity ETFs and 4,887 stocks from July 2006 to December 2013, we show that ETFs contribute to equity return comovement. An ETF-level analysis reveals that the higher turnover an ETF has, the more its component stocks move together at monthly frequency, controlling for time trends, fund- and time-fixed effects, in addition to a host of fund-level control variables.[4]

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[1]See: http://www.icifactbook.org/fb_ch3.html

[2]The transparency of an ETF's holdings make such arbitrage possible. According to Investor Company Institute Website, 'ETFs contract with third parties (typically market data vendors) to calculate an estimate of an ETF's Intraday Indicative Value (IIV), using the portfolio information an ETF publishes daily. IIVs are disseminated at regular intervals during the trading day (typically every 15 to 60 seconds). Some market participants for whom a 15- to 60-second latency is too long will use their own computer programs to estimate the underlying value of the ETF on a more real-time basis.'

[3]Greenwood (2008) that takes advantage of the index weighting scheme is a notable exception.

[4]Fund fixed effects alleviate the selection bias that arises when similar stocks are selected by the same ETF. Time fixed effects are also crucial since both ETF activities and stock comovement can be driven by the same macroeconomic variables. For example, Forbes and Rigobon (2002) show that equity correlation tends to increase during volatile periods when the trading volumes are also high.

To alleviate concerns that a common trend in both ETF activity and return comovement drives their link, we also include an interaction term between the fund fixed effect and a time trend. Finally, our analysis also corrects for cross-correlation in error terms arising from common holdings across ETFs.

At the fund level, a one-standard-deviation increase in the turnover of a typical ETF in our sample is associated with a 1% increase in the average correlation among its component stocks. This relationship is not driven by ETFs on large indices with futures and options traded.[5] This effect is stronger among larger ETFs and ETFs that are often traded simultaneously with their underlying stock portfolios, supporting our conjecture that the comovement is driven by arbitrage between ETFs and the underlying stock portfolios.[6]

ETF arbitrage can occur in a different form via ETF creation and redemption activity. Consider the case when an ETF is trading at a discount, the authorized participants (APs) could buy the ETF shares and sell short the underlying securities. At the end of the day, APs return the ETF shares to the fund in exchange for the ETF's redemption basket of securities, which they use to cover their short positions. We find that our measure of creation and redemption activity is less strongly related to comovement than are ownership or turnover. This is not surprising as APs can borrow the underlying shares from or return these shares to large institutional investors such as pension funds without actually trading the underlying shares and causing excessive correlations.

A key challenge is that the stocks in the same ETF may comove due to their common exposures to fundamental shocks. To better control for fundamentals-driven return comovement, we focus on a ‘discontinuity’ between two stock indices, namely, the large-cap S&P100 index and the mid-cap S&P400 index which together combine to form the S&P500 index. At the end of each month, we define three portfolios: Portfolio A contains the smallest stocks in the S&P100; Portfolio B contains the largest stocks in the S&P400 and Portfolio C contains the remaining S&P400 stocks. We model the next-month daily returns on these three portfolios using the framework of Greenwood and Thesmar (2011). Since Portfolios A and B contain similar stocks by construction, the covariance between their return spread and the return on Portfolio C should more cleanly isolate correlated trading induced by arbitrage activities on the S&P400 index ETFs. Indeed, we find this covariance to significantly load on measures of activities on the S&P400 index ETFs. In addition, the average stock correlation in Portfolio B is strongly linked to the turnover on the S&P400 index ETF, even after controlling for the average stock correlation in Portfolio A. The evidence suggests that return comovement is driven by common ETF membership, rather than general demand for the market portfolio or other fundamental factors that may result in correlated trading in similar stocks.

We also conduct our analysis at the stock level. While arbitrage trading on one ETF only makes a stock in that ETF comove more with the stock basket underlying the same ETF, the average stock in our sample is held simultaneously by 26 ETFs. As such, when the average arbitrage activity on these 26 ETFs increases, we expect a stock to comove more with its ‘super-portfolio’ that holds all 26 underlying stock baskets. Empirically, we find the stock's beta with respect to its ‘super-portfolio’ to highly correlate with the stock's CAPM beta with a correlation coefficient of

[5]Only three indices have futures, options or futures options traded on them during our sample period. They are S&P500, NASDAQ 100 and Dow Jones Industrial Average. Out of the 549 ETFs in our sample, only 7 are based on these three indices.

[6]We do not use the daily difference between ETF price and ETF NAV as a proxy for arbitrage trading for two reasons. First, there is a potential non-synchronicity issue between the ETF price and its NAV, making their difference a noisy measure of mispricing. Second and more importantly, a price difference can reflect either an actual opportunity for arbitrage trade or the presence of limits-to-arbitrage.

0.90. For this reason, we link the activities of all ETFs holding the stock to the stock's CAPM beta in our analysis.[7]

First, we find that the higher the total ETF ownership of a stock, the more it comoves with the market in the subsequent month. This holds controlling for stock and time fixed effects and a host of stock-level control variables. For example, a 1%-of-market-capitalization increase in total ETF ownership of a stock is associated with an increase of 0.03 in beta. Importantly, the effect of ETF holdings is more than three times larger than the effect of mutual fund holdings or other institutional holdings of the stock.

Second, as in the fund-level analysis, we also find that the stock's exposure to ETF turnover is related to how much the stock comoves with the market. A one-standard-deviation increase in weighted average turnover is associated with an increase of 0.09 in a stock's CAPM beta, again controlling for other effects. Finally, the effect of ETF activities on stock comovement is stronger among small stocks and stocks with low turnover.

Given the evidence for a positive link between ETF activities and return comovement, the natural question is: does the increased return comovement reflect faster incorporation of systematic information in the market that ETF trading helps to facilitate; or does it also contain 'excessive' price movement due to non-fundamental shocks that ETF trading helps to propagate? We note that if price movement reflects correlated price pressure rather than fundamental information, to the extent that the price pressure is temporary, we should observe subsequent price reversals on both the ETF and the individual stock.

We examine this important question at the fund and stock levels. At the fund level, we find the ETF's daily returns to be negatively autocorrelated and such an autocorrelation to be more negative when the ETF turnover is higher, consistent with the notion that ETF prices may at times contain 'noise' that triggers ETF arbitrage. At the stock-level, we examine lagged market betas. Empirically, we find that stocks with higher measures of ETF activity tend to have significantly negative betas on lagged market returns, and that a stock's lagged betas on market returns are negatively related to the activity of ETFs owning the stock. This suggests that ETF activity is related to overshooting and reversals in prices, a symptom of 'excess' comovement. In sharp contrast, if ETFs only speed up incorporation of common information, the lagged betas should not be negative.

Our paper is related to the large literature on return comovement in many asset classes. In addition to examining equity market indices, Barberis & Shleifer (2003) and Peng & Xiong (2006) argue that categorical learning and investing by investors could lead to excessive comovement among stocks with similar characteristics or styles. ETFs, by making it easier to trade stocks with similar characteristics, could potentially contribute to style-based return comovements. Finally, a recent literature has linked correlated institutional ownership and trading to excessive return comovement. Examples include Greenwood & Thesmar (2011), Anton & Polk (2014) and Bartram, Griffin, Lim, & Ng (2015). To the extent that institutions have some discretion in deciding when and what to trade, ETF arbitrage is more likely to drive return comovement among its component stocks. Indeed, while the ETF holdings of stocks are smaller relative to that of other institutional investors, we find the impact of ETF arbitrage on return comovement to be much larger.

Our paper is also related to the growing literature on ETFs. Boehmer & Boehmer (2003) find that the initiation of trading of three ETFs on the NYSE increased liquidity and market quality. Hamm

[7]We also repeat our analysis using the stock's beta with respect to its 'super-portfolio' precisely defined or after excluding ETFs holding fewer than 100 stocks. The results are very similar and are reported in the online Appendix.

(2011) finds a positive relationship between ETF ownership percentage and a stock's liquidity, especially for stocks held by highly diversified ETFs. Engle & Sarkar (2002), Petajisto (2017), and Marshall, Nguyen, & Visaltanachoti (2012) focus on the drivers of differences between the market price of the ETF and the price of the underlying portfolio, and Jiang & Yan (2012) investigate levered ETFs. Our paper extends this stream of literature by examining the impact of ETF-underlying arbitrage on return comovement.

A recent study by Ben-David, Franzoni, & Moussawi (2017) provides interesting examples where arbitrage activity propagates liquidity shocks from ETFs to the underlying stocks and increases volatility, but does not investigate stock comovement. In another contemporaneous study using proprietary daily holdings data on 12 ETFs, Staer (2012) confirms the positive relationship between ETF turnover and return comovement at higher frequency. In contrast to his tests, our study covers a much broader cross-section including 549 ETFs and 4,887 stocks. The broader coverage allows us to conduct tests at both the fund level and the stock level.

The paper proceeds as follows. The following section presents the data used in the study. Section 3 presents the empirical link between various ETF activities and return comovement at both the fund- and stock-level. Section 4 confirms that at least part of such return comovement is excessive, and the last section concludes. We collect additional empirical results in the online Appendix.

## 2 | DATA

Although the first ETF began trading in 1980, Figure 1 shows that holdings of exchange-traded funds were a negligible percentage of stocks' shares outstanding prior to mid-2006, so our data begin in July of 2006. We obtain data on all exchange-traded funds from the CRSP stock database identified by their share code of 73. As ETFs are securities according to the CRSP stock database and funds according to the CRSP Survivor-Bias-Free Mutual Fund database, we can obtain both the fund's price information and its holdings information, which we match by cusip. We confirm that the funds are ETFs by retaining only funds with etf_flag of ‘F’ in the CRSP mutual fund database. We further retain only equity ETFs, with Lipper asset code EQ in the CRSP mutual fund database. In addition, we exclude foreign and global ETFs as described by excluding ETFs with a Lipper Class Name containing a country or global region name, or the words ‘global’ or ‘international’. Finally, we read through each ETF name and remove levered and any remaining international ETFs. The levered ETFs are usually very small compared to their unlevered counterparts. ETF shares outstanding data are from Morningstar, which is more precise on a daily basis than the *shrout* variable from CRSP. When shares outstanding is missing in Morningstar, we use CRSP *shrout*.

We also obtain information on the stocks held by ETFs. We use the CRSP mutual fund holdings database because few ETFs are linked to the Thompson holdings database by the MFLinks linking database. Since portfolios are disclosed quarterly, on any given day the estimate of portfolio holdings is the latest quarterly disclosure multiplied by the number of shares outstanding today and divided by the number of shares outstanding at the time of disclosure.[8] Some fund families, like Vanguard, use the same overall portfolio (crsp_portno) to disclose holdings by their mutual funds and ETFs together (various crsp_fundnos) Thus, for disclosure purposes, they treat the ETF as a separate share class of their traditional mutual fund. To capture only the ETF holdings, we use the assets under management in the ETFs and multiply by the percentages of the holdings in the overall portfolio. The median ETF in our sample turns over its portfolio only 0.25 times per year, which reflects that ETFs rarely change the

[8]Using unadjusted holdings of the latest quarterly disclosure does not change the nature or significance of our results.

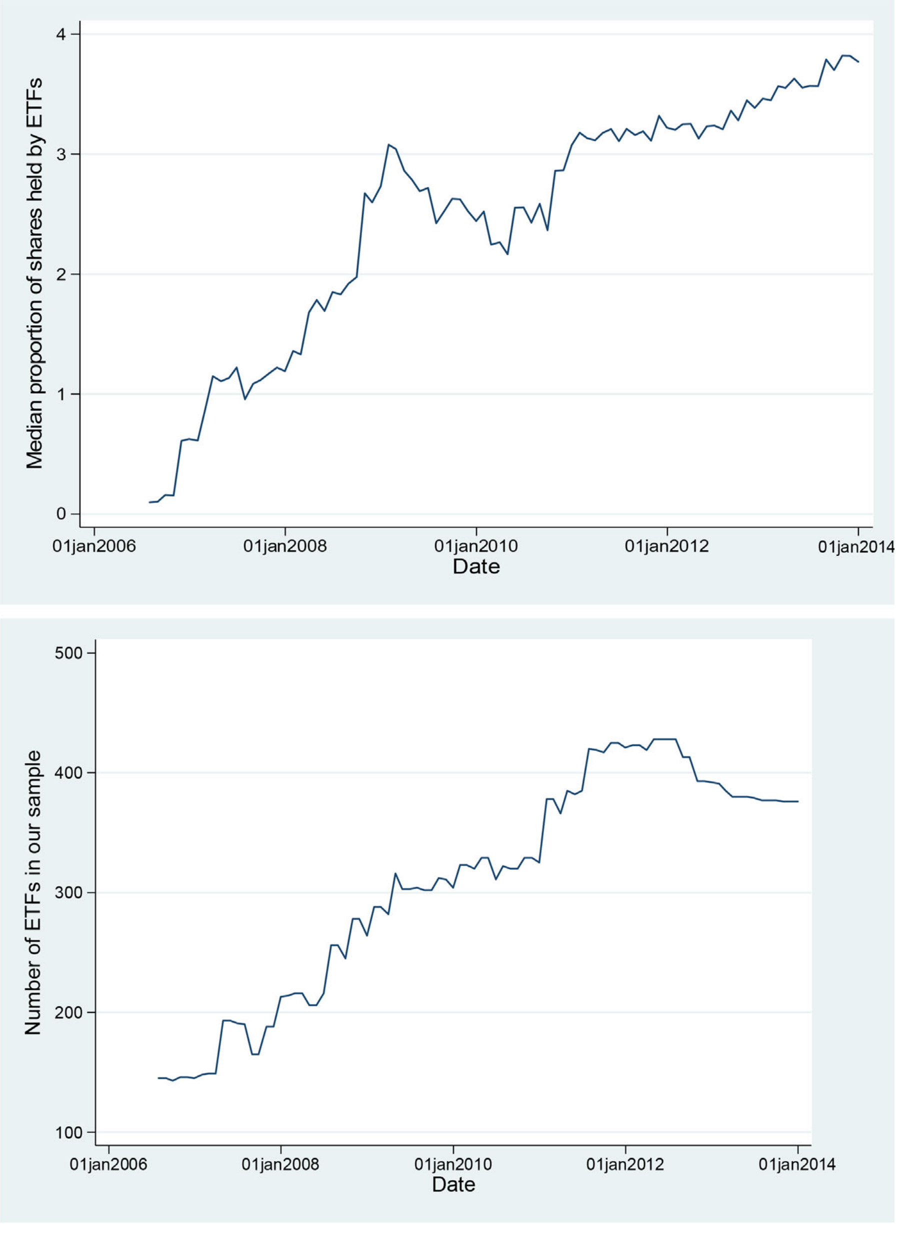



**FIGURE 1** **Growth of ETF market.** The top figure presents the median of the percentage of the stock that is held by exchange traded funds for CRSP stocks with share price of at least US$ 5 and market capitalization of at least US$ 100 million. The bottom figure presents the number of ETFs in our sample each month. The sample consists of purely domestic equity ETFs.

composition of their portfolios. As such, holdings observed at the beginning of the quarter should measure the ETF portfolio composition during the quarter quite well. Our final sample consists of 549 US equity ETFs with holdings data. Consistent with the growth of the ETF sector during our sample period, the number of ETFs in our final sample grows from 145 in 2006 to 376 in 2013 (see Figure 1). Figure 1 also shows that ETF holdings for an average stock in our final sample grew fast as well. While we can identify the inception and closure dates for many ETFs during our sample period, we do not use them to study the impact of ETF activities on return comovement in an event study framework. A careful examination of these inceptions and closures reveals that they are often endogenous events. In addition, the ETF activities tend to pick up very gradually since inception and ETFs are often inactive before their closures.

We limit our stock-level data to all stocks in CRSP with share codes 10 and 11 that have a market capitalization of US$ 100 million dollars or more and a share price of US$ 5 or more. Quarterly book values are from the Compustat database. Our final sample consists of 4,887 stocks. Among them, 4,318 stocks are held by at least one ETF during our sample period.

Summary statistics on monthly data for ETFs in our sample appear in Table 1, Panel A. The average ETF in our sample holds about 0.113% of the total market capitalization of its underlying portfolio. The median fund holds 0.014% of its underlying portfolio. Thus, 549 such ETFs add up to a non-trivial proportion of the market capitalization of the stocks they own. Moreover, the turnover of the funds, which averages 3% per day, is large compared to the turnover of the underlying stocks, which averages 1% per day (see Table 1, Panel B).

The median total net assets (TNA) of the ETFs in our sample is US$ 100 million but the average is larger, at US$ 1,221 million. This is due to a few large ETFs such as State Street's SPY ETF, which tracks the S&P500 index. The stock-level analysis includes a S&P500 membership indicator variable in addition to stock fixed effects to ensure that the results are not due to S&P500 membership and thus inclusion in some of these large ETFs. Consistent with ETFs being inexpensive to manage, expense ratios are very low, averaging half a percent per year. *N holdings* is the number of holdings of common stock in the fund's reported portfolio that can be matched to our stock sample. These funds hold an average of 261 stocks (median is 88) that pass the stock screens described above.

Table 1, Panel B presents summary statistics for stocks in our sample. The mean and median ETF holdings of these stocks are more than 2.3%, comparable to the holdings by index funds. While the average ETF holding is small relative to that of the mutual funds (22.51%) and other institutions (43.22%), it has been growing exponentially in the recent past as evident in Figure 1. As a result, it is common for a stock to be held by multiple ETFs. In fact, the average stock in our sample is held by 26.38 ETFs and more than 25% of our sample stocks are each held by more than 39 ETFs. It is therefore crucial to include a broad cross-section of ETFs when measuring a stock's exposure to ETF activities.

## 3 | ETF ACTIVITIES AND RETURN COMOVEMENT

We first examine whether ETF activities are related to return comovement among component stocks at the fund level. We then exploit the discontinuity between the S&P100 and the S&P400 indices. Finally, we investigate whether ETF activities affect comovement with the market portfolio at the stock level.

### 3.1 | Fund-level tests

In this subsection, we test whether an ETF's greater ownership of its underlying portfolio, creation and redemption activity, and turnover are related to the return correlations of its underlying stocks. We describe the measures of fund-level average return correlation and ETF activity below.

**TABLE 1** Summary statistics

Panel A presents summary statistics of monthly ETF-level data for 549 ETFs. *Fratio* is the ratio of the variance of the portfolio to the average of the variances of the stocks in the portfolio. *Holdings %* is the proportion of the portfolio's total market capitalization that is owned by the ETF on the last day of the prior month. *SD shares* is the standard deviation of ETF shares outstanding. *ETF turnover* is the average daily turnover of ETF shares. *Expense ratio* is the annual expense ratio of the fund, in percent. *TNA* is total net assets of the fund as of the latest report, in millions of dollars. *N holdings* is the number of the ETF's holdings of common stock that are also in our CRSP stock sample.
Panel B presents stock-level summary statistics for 4,887 stocks. $\beta_M$ is the coefficient of the stock's daily excess returns on daily market excess returns in that month. $\beta_{SENT}$ is the sentiment beta. *ETF %* is the proportion of the stock that is held by ETFs, using CRSP data, on the last day of the prior month. *Wtd SD* is the weighted average percentage standard deviation in the shares outstanding of the ETFs that hold the stock. *Wtd turnover* is the weighted average turnover of the ETFs that hold the stock. *Stock turnover* is the average daily turnover of the stock over the month *Log(Mkt cap)* is the log of the firm's market capitalization. *B/M* is the book-to-market ratio. *S&P500* is an indicator variable for whether the stock is currently in the S&P500 index. *Index %* is the percentage of stock held by index funds. *MF %* and *Ins.%* are the percentage of the stock held by mutual funds and by other institutions. *N ETF holders* is the number of ETFs that hold the stock. Detailed variable definitions are given in Appendix A.

| **Panel A: Fund-level variables** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ***Variable*** | **Mean** | **SD** | **p1** | **p25** | **p50** | **p75** | **p99** | **N** |
| *Fratio* | 0.419 | 0.180 | 0.118 | 0.277 | 0.390 | 0.547 | 0.849 | 27,693 |
| *Holdings %* | 0.113 | 0.254 | 0.000 | 0.003 | 0.014 | 0.076 | 1.419 | 27,693 |
| *SD shares* | 0.022 | 0.040 | 0.000 | 0.000 | 0.008 | 0.026 | 0.236 | 27,693 |
| *ETF turnover* | 0.030 | 0.066 | 0.001 | 0.005 | 0.010 | 0.021 | 0.436 | 27,693 |
| *Expense ratio* | 0.004 | 0.002 | 0.001 | 0.003 | 0.005 | 0.006 | 0.009 | 24,004 |
| *TNA* | 1,221 | 5,423 | 2 | 24 | 100 | 443 | 16,683 | 26,892 |
| *N holdings* | 261 | 448 | 3 | 35 | 88 | 281 | 2,010 | 27,693 |
| **Panel B: Stock-level variables** | | | | | | | | |
| **Variable** | **Mean** | **SD** | **p1** | **p25** | **p50** | **p75** | **p99** | **N** |
| $\beta_M$ | 1.170 | 0.753 | −0.673 | 0.694 | 1.111 | 1.590 | 3.529 | 241,843 |
| $\beta_{SENT}$ | 0.01 | 0.07 | −0.205 | −0.025 | 0.007 | 0.044 | 0.227 | 15,061 |
| *S Ratio* | 2.494 | 1.664 | 1.037 | 1.440 | 1.935 | 2.888 | 10.441 | 241,843 |
| *ETF %* | 2.662 | 2.066 | 0 | 1.056 | 2.375 | 3.894 | 9.214 | 241,843 |
| *Wtd. SD* | 0.027 | 0.023 | 0 | 0.010 | 0.020 | 0.036 | 0.113 | 241,843 |
| *Wtd. turnover* | 0.113 | 0.103 | 0 | 0.031 | 0.088 | 0.160 | 0.479 | 241,843 |
| *Stock turnover* | 0.010 | 0.012 | 0.000 | 0.004 | 0.007 | 0.013 | 0.052 | 241,843 |
| *Log (Market cap)* | 20.86 | 1.55 | 18.50 | 19.65 | 20.64 | 21.81 | 25.20 | 241,778 |
| *B/M* | 0.610 | 0.918 | 0.035 | 0.277 | 0.476 | 0.754 | 2.48 | 227,905 |
| *S&P500* | 0.173 | 0.378 | 0 | 0 | 0 | 0 | 1 | 241,843 |
| *Index %* | 3.049 | 2.165 | 0 | 0.553 | 2.362 | 4.559 | 6.961 | 195,490 |
| *MF %* | 22.51 | 13.63 | 0 | 11.92 | 21.79 | 31.73 | 56.40 | 241,843 |
| *Ins.%* | 43.22 | 18.46 | 0 | 31.37 | 44.03 | 55.57 | 84.26 | 241,843 |
| *N ETF holders* | 26.38 | 19.22 | 0 | 12 | 22 | 39 | 77 | 241,843 |

### 3.1.1 | Empirical measures

We define the fund-level variance ratio (*Fratio*) as follows:

$$Fratio = \frac{\text{Variance of the average daily return of the stocks in the portfolio}}{\text{Average of the variances of the returns of stocks in the portfolio}}. \tag{1}$$

This ratio is computed each month for each ETF. According to equation (10) of Pollet & Wilson (2008), *Fratio* is a measure of average correlation among stocks in the portfolio. For intuition, consider an equal-weighted portfolio containing $N$ stocks, the portfolio return variance during any period $t$, $\sigma^2_{p,t}$, is related to individual stock return volatilities ($\sigma_{j,t}$ and $\sigma_{k,t}$) and their pairwise correlations ($\rho_{jk,t}$) as:

$$\sigma^2_{pt} \sum_{j=1}^{N} \sum_{k=1}^{N} \frac{1}{N^2} \rho_{jk,t} \sigma_{j,t} \sigma_{k,t} = \bar{\sigma}^2_t \bar{\rho}_t + \sum_{j=1}^{N} \sum_{k=1}^{N} \frac{1}{N^2} \rho_{jk,t} \xi_{jk,t}, \tag{2}$$

where:

$$\bar{\sigma}^2_t \frac{1}{N} \sum_{j=1}^{N} \sigma^2_{j,t}, \tag{3}$$

$$\bar{\rho}_t \frac{1}{N^2} \sum_{j=1}^{N} \sum_{k=1}^{N} \rho_{jk,t}, \tag{4}$$

$$\xi_{jk,t} \sigma_{j,t} \sigma_{k,t} - \bar{\sigma}^2_t. \tag{5}$$

Pollet & Wilson (2008) show that the product between the average variance and the average correlation (the first term in the RHS of equation (2)) explains more than 97% of the variation in the portfolio return variance (the LHS of equation (2)). It then implies that the ratio between portfolio return variance and average stock return variance as in *Fratio* should be the main driver of the average stock correlation. In fact, *Fratio* is identical to the average stock correlation in the special case where all stocks have the same variance (so the second term in the RHS of equation (2) disappears). Throughout the paper, we winsorize our dependent variables at the 1% level in the regressions to remove the effect of outliers.[9] Table 1, Panel A shows that *Fratio* has a mean of 0.42 and median of 0.44.

We use three measures of ETF activity at the portfolio level. The first measure is the proportion of the underlying portfolio that is held by the ETF, *Holdings%*. This is equal to the market capitalization of the ETF divided by the total market capitalization of all stocks in its underlying portfolio.

The second measure of ETF activity is the standard deviation of the daily number of shares outstanding of the ETF, divided by the mean shares outstanding during the month, *SD shares*. This is meant to capture the intensity of the creation and redemption activity of the ETF, and therefore the volatility associated with the demand for the underlying stocks of the ETF. Creation and redemption could drive underlying stock correlations if authorized participants (APs) need to buy and sell large parts of the portfolio together when they create or redeem shares, but since creation and redemption

[9]The winsorization has little effect on *Fratio* since it is already bounded between 0 and 1.

occurs only once a day and is thus unlikely to be used in arbitrage, there is less urgency for the entire portfolio to trade together. Panel A of Table 1 shows that the daily standard deviation of shares outstanding averages 2.2% of ETF shares outstanding per day. The median is smaller at 0.8%.

A third measure of ETF activity is *ETF turnover*. This is the average over the month of the ratio of the daily number of shares traded to the number of shares outstanding that day. This will be positively related to the amount of arbitrage activity in the ETF, although there are clearly other reasons to trade the ETF besides arbitrage of its price relative to its components' prices. Table 1, Panel A shows that ETF turnover averages 3% per day.

One would naturally expect the impact of *SD shares* and *ETF turnover* on return correlation to depend on the relative size of the ETF measured by *Holdings%*. In other words, an ETF's creation, redemption and trading activities should have a larger impact on its underlying stocks when the ETF's holding represents a bigger share of the underlying stocks' market capitalizations. Hence we also multiply *SD shares* and *ETF turnover* by *Holdings%* in our regressions. Additional subsample analysis in the online Appendix also confirms that *SD shares* and *ETF turnover* have the strongest effect among the top third largest ETFs in our sample.

We use fund and time fixed effects, which subsume many possible control variables such as industry classification, market return and market volatility. In addition, since ETF activities in general are increasing during our sample period as shown in Figure 1, if average stock correlation displays a similar trend due to more correlated fundamentals, we would find spurious correlation between the two. To address such a concern, we also include an interaction term between the fund fixed effect and a time trend. Finally, some controls vary by both fund and time. We include fund size as measured by total net assets (TNA). We also include the number of holdings as a control variable since it can affect portfolio diversification and thus the *Fratio*.

ETFs often hold stocks in common, so regression errors may be correlated in the cross-section.[10] As a result, standard errors that are double-clustered by month and fund, and thus robust to heteroskedasticity and autocorrelation, are not sufficient for our purposes. We follow Driscoll & Kraay (1998) to compute a non-parametric covariance matrix estimator that produces standard errors that are robust to general forms of spatial and temporal dependence.[11] The Driscoll-Kraay standard errors are consistently larger than the (untabulated) double-clustered or Generalized-least-square (GLS) standard errors in our panel regressions.

We also control for the (log) number of ETF's stock holdings in our regressions since it can affect portfolio diversification. To make sure that our results are not driven by ETFs with concentrated holdings, in the online Appendix, we remove all ETFs with number of stock holdings fewer than 100 and find similar results.

### 3.1.2 | Empirical results

In Table 2, we regress the measure of in-portfolio correlation, *Fratio*, on measures of ETF activities and control variables. Panel A presents univariate regressions showing that all measures of ETF activity are

[10]We have tried to combine multiple ETFs that track the same index into one. We are able to find index composition for many ETFs from Compustat, and we hand-matched the indexes to the funds' benchmark indices and cross-checked with the funds' reported holdings. As it turns out, there are only 5 cases of multiple ETFs in our sample tracking exactly the same index: the S&P 500 (3 ETFs), the Dow Jones Industrial Average (2 ETFs), the S&P 400 (3 ETFs), the S&P 600 (4 ETFs), and the Nasdaq 100 (2 ETFs). Not surprisingly, aggregating multiple ETFs on the same index hardly changes our fund-level regression results as the total number of fund observations goes down by only 9.

[11]The Driscoll-Kraay standard error is estimated in Stata using the xtscc program prepared by Driscoll & Kraay (1998).

**TABLE 2** Fund-level tests

Panel A presents fund-month panel regressions that relate three measures of ETF activity to underlying stock return correlations. *Fratio* is the ratio of the variance of the portfolio to the average of the variances of the stocks in the portfolio. *Holdings %* is the proportion of the portfolio's total market capitalization that is owned by the ETF on the last day of the prior month. *SD shares* is the standard deviation of ETF shares outstanding. *ETF turnover* is the average daily turnover of ETF shares.
Additional control variables and fixed effects appear in Panels B and C. *Expense ratio* is the annual expense ratio of the fund, in percent. *TNA* is total net assets of the fund as of the latest report, in millions of dollars. *Log(N holdings)* is the log of the number of the ETF's holdings of common stock that are also in our CRSP stock sample. Detailed variable definitions are given in Appendix A.
We follow Driscoll & Kraay (1998) to compute a non-parametric covariance matrix estimator that produces heteroskedasticity- and autocorrelation-consistent standard errors that are robust to general forms of spatial and temporal dependence.***, ** and * signify statistical significance at the 1%, 5% and 10% levels.

| **Panel A: Baseline** | | | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| | Y = *Fratio* | | | | | |
| *Holdings %* | 0.0447*** | | | 0.0157** | | |
| | (0.00830) | | | (0.00709) | | |
| *SD shares* | | 0.479*** | | 0.249** | | |
| | | (0.109) | | (0.113) | | |
| *ETF turnover* | | | 0.509*** | 0.448*** | | |
| | | | (0.0376) | (0.0489) | | |
| *Holdings %*SD shares* | | | | | 2.217*** | |
| | | | | | (0.269) | |
| *Holdings %*ETF turnover* | | | | | | 8.431*** |
| | | | | | | (1.072) |
| Constant | 0.414*** | 0.409*** | 0.404*** | 0.399*** | 0.414*** | 0.415*** |
| | (0.0209) | (0.0204) | (0.0207) | (0.0205) | (0.0208) | (0.0207) |
| Time FE | NO | NO | NO | NO | NO | NO |
| Fund FE | NO | NO | NO | NO | NO | NO |

(Continues)

**TABLE 2** (Continued)

| Panel A: Baseline | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Observations | 27,693 | 27,693 | 27,693 | 27,693 | 27,693 | 27,693 |
| R-squared | 0.004 | 0.011 | 0.035 | 0.038 | 0.011 | 0.009 |

| Panel B: With additional controls | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Y = *Fratio* | | | | | | | |
| *Holdings %* | 0.0381*** | | | 0.0417*** | 0.0116 | | | 0.00987 |
| | (0.0131) | | | (0.0135) | (0.0160) | | | (0.0155) |
| *SD shares* | | 0.0212 | | −0.0204 | | 0.0103 | | -0.0261 |
| | | (0.0215) | | (0.0237) | | (0.0221) | | (0.0240) |
| *ETF turnover* | | | 0.145*** | 0.155*** | | | 0.140*** | 0.147*** |
| | | | (0.0325) | (0.0358) | | | (0.0302) | (0.0322) |
| *Expense ratio* | −2.776 | −2.777 | −2.449 | −2.421 | 6.274*** | 6.199*** | 7.042*** | 7.134*** |
| | (2.057) | (2.049) | (2.085) | (2.084) | (2.228) | (2.244) | (2.194) | (2.178) |
| *Log(TNA)* | −0.00507** | −0.00336 | −0.00346 | −0.00533** | −0.00478 | -0.00431 | -0.00418 | -0.00458 |
| | (0.00251) | (0.00259) | (0.00254) | (0.00246) | (0.00448) | (0.00436) | (0.00427) | (0.00440) |
| *Log(Nholdings)* | −0.0559*** | −0.0562*** | −0.0559*** | −0.0555*** | −0.0591*** | -0.0591*** | -0.0589*** | -0.0589*** |
| | (0.00950) | (0.00947) | (0.00945) | (0.00947) | (0.00852) | (0.00852) | (0.00848) | (0.00848) |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE*Fund FE | NO | NO | NO | NO | YES | YES | YES | YES |
| Fund FE | YES | YES | YES | YES | YES | YES | YES | YES |

(Continues)

**TABLE 2** (Continued)

**Panel B: With additional controls**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Observations | 23,813 | 23,813 | 23,813 | 23,813 | 23,813 | 23,811 | 23,813 | 23,813 |
| R-squared | 0.748 | 0.7638 | 0.765 | 0.7655 | 0.7863 | 0.7863 | 0.7864 | 0.7865 |

**Panel C: With interaction terms**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Y = *Fratio* | | | |
| *Holdings %*SD shares* | 0.161 | | 0.0636 | |
| | (0.144) | | (0.146) | |
| *Holdings %*ETF turnover* | | 1.501*** | | 1.375** |
| | | (0.565) | | (0.679) |
| *Expense ratio* | −2.680 | −2.666 | 6.525*** | 6.596*** |
| | (2.063) | (2.069) | (2.259) | (2.291) |
| *Log(TNA)* | −0.00355 | −0.00368 | −0.00426 | −0.00450 |
| | (0.00259) | (0.00259) | (0.00436) | (0.00437) |
| *Log(Nholdings)* | −0.0562*** | −0.0562*** | −0.0592*** | −0.0593*** |
| | (0.00948) | (0.00949) | (0.00851) | (0.00847) |
| Time FE | YES | YES | YES | YES |
| Time FE*Fund FE | NO | NO | YES | YES |
| Fund FE | YES | YES | YES | YES |
| Observations | 23,811 | 23,811 | 23,811 | 23,811 |
| R-squared | 0.7638 | 0.765 | 0.7863 | 0.7864 |

positively and significantly related to *Fratio* if no fixed effects and additional controls are included. Panel B presents the regressions with various fixed effects and control variables. Columns (1)–(4) have only time and fund fixed effects and columns (5)–(8) also include the interaction term between the fund fixed effect and a time trend. When time and fund fixed effects are included, *SD shares* becomes no longer significant (columns (2) and (4)). When the time trend term is also added, *Holdings%* is no longer significant either. In contrast, *ETF turnover* is significant in all regression specifications.

In column (8), all three explanatory variables appear together with fixed effects and controls. This column shows that the strongest predictor of how much the stocks in the portfolio co-move is the daily turnover of the ETF. A one-standard-deviation increase (0.066) in the daily turnover of an average ETF in our sample is associated with a 0.147*0.066 = 0.01 increase in the *Fratio* of the stocks in its portfolio. This amounts to 5.4% of its standard deviation.

When fixed effects are included, *Holdings%* and *SD shares* are no longer significant while *ETF turnover* still is. The result helps to make two points. First, the result suggests that ETF arbitrage as proxied by *ETF turnover* most likely drives return correlations. Creation and redemption activity is less important, which is not surprising as they can be carried out without trading the underlying securities. In other words, ETF arbitrage drives return correlations only when trading of the underlying stocks is involved. Second, the fact that *ETF turnover* remains highly significant after controlling for *Holdings%* and *SD shares* alleviates concerns that changing stock comovement may reflect time varying style preference (see Barberis & Shleifer, 2003; and Peng & Xiong, 2006). For example, an increase in investors' interest in value stocks may result in more comovement among stocks in a value ETF. Such a changing investor style preference, however, should be reflected in *Holdings%* and *SD shares* since an increase in investors' interest in value stocks will result in creation of new shares of ETFs specializing in value stocks, thus leading to increases in both *Holdings%* and *SD shares*.

The impact of ETF activity on underlying stock return correlations is not equal across ETFs. Larger ETFs, by holding bigger fractions of the total market capitalization of their underlying stocks, could drive the stock correlations more. To test this conjecture, in Panel C, we interact *SD shares* and *ETF turnover* by *Holdings%* in our regressions. Again, we find only *Holdings%***ETF turnover* to be significant, consistent with the notion that arbitrage trading on larger ETFs is more likely to generate return comovement.

It is important to note that ETF turnover on its own should not generate higher stock correlations. ETF turnover affects stock correlations only insofar as it is positively related to equivalent turnover in the underlying stocks via arbitrage trades. This could be a direct effect where a large part of the turnover is arbitrage-driven, or an indirect effect, where increased investor trading of ETFs creates price differences and drive arbitrage activity. In such arbitrage trades, ETF turnover and the underlying stock turnover should occur simultaneously, which motivates our second subsample cut. Each month, we regress each ETF's daily turnover on the average daily turnover of its underlying stocks and compute the $R^2$ of the regression. Intuitively, the $R^2$ measures the extent to which ETF trading drives trading in the underlying stocks. A high $R^2$ indicates more simultaneous trading in both the ETF and its underlying stocks, such that *ETF turnover* more likely reflects arbitrage trading and affects stock correlations. Table 3, Panel A confirms that *ETF turnover* has a higher coefficient among the tercile of ETFs with the highest $R^2$s.

Last, since the success of the ETF arbitrage depends on the ability to trade the entire underlying basket at the same time, we expect the arbitrage to be more difficult for ETFs that also hold corporate bonds, municipal bonds, asset-backed securities or mortgage-backed securities which cannot be traded quickly. As a result, stocks in such ETFs should not experience increasing return correlation. Column (2) of Table 3, Panel B examines the subset of 121 ETFs that holds such fixed income assets. In this subset, we find that the coefficient on *ETF turnover* is no longer significant, consistent with the limits-to-arbitrage.

**TABLE 3** Fund-level tests: Subsets

This table presents coefficients from multivariate regressions on monthly data from 2006–2013. The dependent variable is *Fratio*, the ratio of the variance of the portfolio to the average of the variances of the stocks in the portfolio. *Holdings %* is the proportion of the portfolio's total market capitalization that is owned by the ETF on the last day of the prior month. *SD shares* is the standard deviation of ETF shares outstanding. *ETF turnover* is the average daily turnover of ETF shares. Detailed variable definitions are given in Appendix A. All regressions include all control variables and fixed effects in Table 2, Panel B. Panel A breaks the sample into terciles by $R^2$. Panel B presents subsets by type of holdings as described by the CRSP mutual fund database. Column (1) presents the full sample, column (2) presents the subsample of ETFs that hold corporate and municipal bonds (sample size 1,232), column (3) presents the ETFs that hold more than the sample median proportion of common stock, column (4) excludes ETFs that track the S&P500, the Nasdaq or the Dow Jones Industrial Average, column (5) conducts the analysis at quarterly frequency with *Fratio* computed using daily returns, and column (6) conducts the analysis at quarterly frequency with *Fratio* computed using weekly returns. *abs(gap)* is the absolute value of the difference between the fund's reported net asset value and its closing market price. Driscoll & Kraay (1998) standard errors are used, and ***, ** and * signify statistical significance at the 1%, 5% and 10% levels.

**Panel A: Subsample cut I**

| ***Y* = *Fratio*** | **$R^2$, Low** | **$R^2$, Medium** | **$R^2$, High** |
|---|---|---|---|
| *Holdings %* | 0.0252 | 0.0248 | 0.0477** |
| | (0.0189) | (0.0158) | (0.0187) |
| *SD shares* | 0.0222 | 0.00728 | 0.0585* |
| | (0.0373) | (0.0261) | (0.0342) |
| *ETF turnover* | 0.0968* | 0.0631** | 0.184*** |
| | (0.0502) | (0.0282) | (0.0377) |

**Panel B: Subsample cut II**

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
|---|---|---|---|---|---|---|
| | **Full sample** | **bond > 0** | **common ≥ median = 99.67%** | **Excluding large index** | **Quarterly** | **Quarterly** |
| | | | | | $Y = Fratio$ | $Y = Fratio_{5day}$ |
| *Holdings %* | 0.0417*** | 0.0780 | 0.0168 | 0.0415*** | 0.0409* | 0.0427 |
| | (0.0135) | (0.102) | (0.0194) | (0.0136) | (0.0231) | (0.0303) |
| *SD shares* | −0.0204 | −0.244* | −0.0135 | −0.0201 | −0.0412 | 0.00260 |
| | (0.0237) | (0.125) | (0.0258) | (0.0237) | (0.0523) | (0.0571) |

(Continues)

**TABLE 3** (Continued)

| Panel B: Subsample cut II | | | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| | **Full sample** | **bond > 0** | **common ≥ median = 99.67%** | **Excluding large index** | **Quarterly** | **Quarterly** |
| *ETF turnover* | 0.155*** | -0.0705 | 0.174*** | 0.153*** | 0.142* | 0.114 |
| | (0.0358) | (0.300) | (0.0456) | (0.0382) | (0.0745) | (0.0770) |
| *Expense ratio* | −2.421 | 113.0 | −0.714 | −2.608 | −2.802 | −2.074 |
| | (2.084) | (74.10) | (2.595) | (2.124) | (2.711) | (2.994) |
| *Log(TNA)* | −0.00533** | −0.00707 | −0.00409 | −0.00541** | −0.00562* | −0.00387 |
| | (0.00246) | (0.0151) | (0.00273) | (0.00244) | (0.00279) | (0.00388) |
| *Log(Nholdings)* | −0.0555*** | −0.0206 | −0.0566*** | −0.0569*** | −0.0446*** | −0.0449*** |
| | (0.00947) | (0.0268) | (0.01000) | (0.00939) | (0.0136) | (0.0157) |
| Time FE | YES | YES | YES | YES | YES | YES |
| Fund FE | YES | YES | YES | YES | YES | YES |
| Observations | 23,813 | 1,230 | 12,613 | 23,463 | 7,883 | 7,883 |
| $R^2$ | 0.7655 | 0.7199 | 0.7554 | 0.7634 | 0.8148 | 0.7775 |
| Avg abs(gap) | 0.0022 | 0.0054 | 0.0019 | 0.0022 | 0.0022 | 0.0022 |

Column (3) of Table 3, Panel B examines the sample where intraday arbitrage should be relatively easier – when the proportion of common stock is greater than the sample median of 99.67%. In this subset, we find that the coefficient on *ETF turnover* is larger than in the full sample presented in column (1). The last row of this table presents the average absolute value of the gap between NAV and closing price during the sample period. NAV is from the CRSP mutual fund database daily file and closing prices are from the CRSP stock database. This row shows that such a gap is greatest when the ETFs hold fixed income assets, making arbitrage difficult, and the gap is lower in the third column when the ETF is mostly stock, compared to the full sample value of 0.25%. This pattern suggests that a large gap may actually reflect the difficulty of arbitrage rather than an opportunity for arbitrage.

Arbitrage trading between index futures and the underlying stocks could also lead to a higher return comovement among stocks in the same index. In our sample period, futures are only traded on three equity indices: S&P500, Dow Jones Industrial Average (DJI) and the Nasdaq index. Column (4) of Table 3, Panel B examines a subsample of ETFs after excluding all ETFs based on the same three indices. We find the strong link between ETF turnover and the return comovement to be very similar even after removing the impact of futures arbitrage.

If the link between ETF turnover and return comovement comes from correlated price pressure caused by ETF arbitrage, we would expect the link to be weaker if the return comovement is measured over longer horizons since price pressure tends to be short-lived. Column (6) of Table 3, Panel B examines the link between ETF activities and return comovement when *Fratio* is computed using weekly returns in a quarter. When returns are measured over a week instead of a day, the link between ETF turnover and return comovement indeed becomes weaker. The lack of significance is in part driven by conducting the regression at quarterly frequency instead of monthly frequency as evident in column (5) where we use quarterly data but still compute *Fratio* using daily returns. The fact that the link between ETF turnover and return comovement becomes weaker when weekly returns are used is less consistent with the interpretation that the return comovement is driven by fundamentals.

## 3.2 | Evidence from S&P Index ETFs

So far, we establish a strong link between the ETF turnover and the return comovement among the stocks ETFs hold and we find the link to be stronger among ETFs that are easy to arbitrage and ETFs whose turnovers are driven by arbitrage trading. The link is also stronger when comovement is measured with daily returns rather than weekly returns. This evidence supports the notion that the higher return comovement comes from correlated short-term price pressure generated by ETF arbitrage. Nevertheless, we have not ruled out the possibility that underlying stocks have become more correlated due to fundamental reasons, making them more attractive to ETF traders and explaining more ETF turnover.

In this sub-section, we focus on a specific example where we can better control for fundamental-driven return comovement by exploiting the 'discontinuity' between two S&P indices. Specifically, we focus on ETFs tracking the S&P100 index and the S&P400 index. Both indices are value-weighted and together they form the S&P500 index. The S&P100 index covers large-cap stocks while the S&P400 index covers mid-cap stocks.

At the end of each month, we construct three portfolios. Portfolio A contains the bottom 10% of the S&P100 index (the 10 stocks with the smallest market capitalizations). Portfolio B contains the top 10% of the S&P400 index (the 40 stocks with the largest market capitalizations). Portfolio C contains the remaining S&P400 index (the remaining 360 stocks). To the extent that portfolios A and B have similar exposures to fundamental shocks, we can use the return on portfolio B to control for the fundamental-related component in portfolio A's return.

Specifically, following Greenwood & Thesmar (2011), we write the daily return of each portfolio during the next month as the sum of a fundamental component and a price pressure component:

$$R_A = F_A + \lambda D_A, \tag{6}$$

$$R_B = F_B + \lambda D_B, \tag{7}$$

$$R_C = F_C + \lambda D_C, \tag{8}$$

where $\lambda$ and $D$ denote price impact and the demand for the stock, respectively. Their product measures the price pressure on the portfolio due to correlated trading.

Consider the return difference between portfolio B and A: $R_B - R_A$. By construction, portfolios A and B contain similar stocks and should have similar fundamental returns. As a result, their return spread should mostly reflect the difference in their respective price pressure: $R_B - R_A = \lambda(D_A - D_B)$.

We then focus on the covariance between $R_B - R_A$ and $R_C$ in that month. Assuming the differential price pressure $\lambda(D_A - D_B)$ is uncorrelated with the fundamental return of portfolio C, we have:

$$Cov(R_B - R_A R_C) = \lambda^2 Cov(D_B - D_A, D_C). \tag{9}$$

$Cov(D_B - D_A D_C)$ should isolate correlated trading of stocks in the S&P400 index only. This is because correlated trading in stocks in the S&P500 index (or other broader index that contains S&P500 stocks) will simultaneously affect stocks in both portfolios A and B and thus will not show up in $D_B - D_A$ nor contribute to $Cov(D_B - D_A D_C)$. In addition, correlated trading in stocks in the S&P100 index should affect $D_A$, but not $D_B$ and $D_C$ and therefore will not contribute to $Cov(D_B - D_A D_C)$ either.

We have argued that ETF activities (arbitrage and creation/redemption) provide a new source of correlated trading and return comovement. We can now test this notion directly by regressing monthly $Cov(R_B - R_A, , R_C)$ on measures of monthly correlated trading triggered by S&P400 ETFs. There are three S&P400 ETFs (offered by SPDR, Vanguard and iShares accordingly) in our sample during the period from 2006/07 to 2013/12.[12] We examine three measures of ETF-induced correlated trading. The first is $(Holding\%)^2$. If a fixed fraction of the S&P400 ETF portfolio gets traded each month, then the monthly variation in correlated trading is driven by $(Holding\%)^2$. Of course, the fraction of the S&P400 ETF portfolio that is traded varies from one month to the other. To that end, we also consider two more measures of correlated trading: $(Holding\%\ x\ SDshares)^2$ and $(Holding\%\ x\ ETFturnover)^2$ to capture trading induced by ETF creation / redemption or by ETF arbitrage.

The regression results in Table 4, Panel A confirm that ETF activities on the S&P400 index drive the covariance between $R_B - R_A$ and $R_C$. A one standard deviation increase in the ETF activity measures leads to an increase of the covariance by about 0.21 to 0.34 of its standard deviation. When we examine the regression beta of $R_B - R_A$ on $R_C$ as the dependent variable, we find similar results.

Finally, we link the evidence from S&P Index ETFs back to the main fund-analysis in Table 2 by examining the same *Fratio* variable as the stock comovement measure. Specifically, we regress the *Fratio* on portfolio B ($Fratio_B$) on measures of activities on the S&P400 index ETFs and the *Fratio* on portfolio A ($Fratio_A$). In other words, we use the stock comovement in portfolio A to control for

[12]There are also levered ETFs based on S&P400 that we exclude from our sample. Their total market capitalization is only 1% of the unlevered S&P400 ETFs.

**TABLE 4** Evidence from S&P Index ETFs

This table presents evidence from S&P Index ETFs. At the end of each month, we construct three portfolios: Portfolio A contains the bottom 10% of the S&P100 index (the 10 stocks with the smallest market capitalizations); Portfolio B contains the top 10% of the S&P400 index (the 40 stocks with the largest market capitalizations); Portfolio C contains the remaining S&P400 index (the remaining 360 stocks). In Panel A, we compute the covariance between $R_B - R_A$ and $R_C$ in the next month using daily returns. We then regress monthly $Cov(R_B - R_A, R_C)$ on measures of monthly correlated trading triggered by S&P400 ETFs. The three measures are $(Holding\%)^2$, $(Holding\% \times SDshares)^2$ and $(Holding\% \times ETFturnover)^2$. We also examine $\beta_{B-A,C}$ defined as $Cov(R_B - R_A, R_C)/Var(R_C)$ as the dependent variable. Both the dependent and independent variables are demeaned and standardized so the regression coefficient can be interpreted as the impact of one standard deviation change in the independent variable. In Panel B, we regress the *Fratio* on portfolio B ($Fratio_B$) on measures of activities on the S&P400 index ETFs and the *Fratio* on portfolio A ($Fratio_A$). In other words, we use the stock comovement in portfolio A to control for fundamental-driven stock comovement in portfolio B. The sample period is from 2006/07 to 2013/12 so the regressions have 90 monthly observations. The White's heteroscedasticity-consistent standard errors are computed and ***, ** and * signify statistical significance at the 1%, 5% and 10% levels.

| Panel A: Regressions I | | | |
|---|---|---|---|
| ***(Holding %)$^2$*** | ***(Holding % x SDshares)$^2$*** | ***(Holding % x ETF turnover)$^2$*** | **$R^2$** |
| Y = $Cov(R_B - R_A, R_C)$ | | | |
| 0.3388*** | | | 0.1148 |
| (0.0962) | | | |
| | 0.2197*** | | 0.0483 |
| | (0.0697) | | |
| | | 0.2927*** | 0.0857 |
| | | (0.0739) | |
| Y = $\beta_{B-A,C}$ | | | |
| 0.4825*** | | | 0.2329 |
| (0.0903) | | | |
| | 0.2925*** | | 0.0856 |
| | (0.0691) | | |
| | | 0.3291*** | 0.1083 |
| | | (0.0945) | |

| Panel B: Regressions II | | | | | |
|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| Y = $Fratio_B$ | | | | | |
| *Holding %* | –0.0088 | | | | |
| | (0.02778) | | | | |
| *SD shares* | | 1.6630* | | | |
| | | (0.8865) | | | |
| *ETF turnover* | | | 3.7362*** | | |
| | | | (0.7478) | | |
| *Holdings %*SD shares* | | | | 0.9629* | |

(Continues)

**TABLE 4** (Continued)

| Panel B: Regressions II | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | | (0.5602) | |
| *Holdings %*ETF turnover* | | | | | 1.1501*** |
| | | | | | (0.3804) |
| $Fratio_A$ | 0.8085*** | 0.8074*** | 0.6568*** | 0.8067*** | 0.7489*** |
| | (0.0609) | (0.0569) | (0.0586) | (0.0565) | (0.0545) |
| R-squared | 0.7024 | 0.7024 | 0.7608 | 0.7088 | 0.7224 |

fundamental-driven stock comovement in portfolio B since stocks in the two portfolios are very similar in fundamentals. If we still find a significant link between the stock comovement in portfolio B and activities on the S&P400 index ETF, it must come from the correlated price pressure channel. Indeed, results in Table 4, Panel B confirm a strong and significant link between turnover on the S&P400 index ETFs and the $Fratio_B$. The link between ETF creation and redemption activities and $Fratio_B$ is also marginally significant but much weaker.

## 3.3 | Stock-level tests

So far, our fund-level results confirm a strong link between ETF arbitrage and return comovement among the stocks held by that ETF and this link does not seem to be driven by correlated fundamentals at least among the ETFs based on S&P indices. We then turn our attention to stock-level analysis. ETF arbitrage could also impact an individual stock's comovement with the market. This is because the average stock in our sample is held simultaneously by 26 ETFs. Arbitrage activity on these 26 ETFs can increase the stock's comovement with a broad portfolio of stocks underlying the 26 ETFs. We test this prediction using stock-level data.

### 3.3.1 | Empirical measures

For each stock each month, we first define its ‘super-portfolio’ by first identifying all ETFs holding the stock and then value-weighting all stock portfolios underlying these ETFs. As a result, different stocks are associated with different ‘super-portfolios’. A natural measure of stock return comovement is the stock's beta with respect to its ‘super-portfolio’ computed using daily excess returns in that month. Nevertheless, we focus on the results using the stock's CAPM beta instead of the ‘super-portfolio’ betas for two reasons.[13] First, these two betas are highly correlated with a correlation coefficient of 0.90 among stocks in our sample. This is not surprising since the ‘super-portfolio’ typically contains a large number of stocks and therefore its return closely tracks that of the market. Second and more importantly, the CAPM beta has been the standard measure in the return comovement literature and is widely used in many other applications, which allows us to better gauge the economic impact of our results. The results from using the ‘super-portfolio’ beta are very similar and are reported in the online Appendix. In addition, we note that if an ETF holds very few stocks, then its underlying portfolio could be very different from the market portfolio. As a result, arbitrage trading on that ETF is less likely to increase the CAPM beta of its component stock. To ensure that these ETFs with concentrated holdings

[13]Specifically, the monthly CAPM beta is the beta obtained from a regression of daily excess stock returns on daily excess market returns provided by Kenneth French's website.

are not driving a spurious link between a stock's exposure to ETF activities and its CAPM beta, in the online Appendix, we also rerun the stock-level tests after removing all ETFs holding fewer than 100 stocks from our sample and we find very similar results.

We have three measures of ETF activity at the stock level. The first measure, *ETF%*, is the proportion (in percentage) of the stock's outstanding shares that are held by all ETFs in our sample. This is computed using the holdings data in the CRSP mutual fund database. The second measure, *Wtd SD*, is the weighted average (by the proportion of the stock they hold) of the standard deviation of shares outstanding of the ETFs holdings the stock. In other words, we compute the stock-level measures by value-weighting the three fund-level activity measures in section 3 across all ETFs holding the stock:

$$Wtd\,SD_{i,t} = \frac{\sum_{j=1}^{N} w_{i,j,t} SD\,shares_{j,t}}{\sum_{j=1}^{N} w_{i,j,t}}, \tag{10}$$

where $j$ indexes the ETF, $i$ indexes the stock, $w_{i,j,t}$ is the weight held by ETF $j$ in stock $i$ at time $t$, and $N$ is the number of ETFs holding the stock.

The third measure of ETF activity, *Wtd turnover*, is the weighted average of the turnover of the ETFs holding the stock:

$$Wtd\,turnover_{i,t} = \frac{\sum_{j=1}^{N} w_{i,j,t} ETF\,turnover_{j,t}}{\sum_{j=1}^{N} w_{i,j,t}}. \tag{11}$$

Here again, $j$ indexes the ETF, $i$ indexes the stock, $w_{i,j,t}$ is the weight held by ETF $j$ in stock $i$ at time $t$, and $N$ is the number of ETFs holding the stock.

We note that both *Wtd SD* and *Wtd turnover* are proxies for ETF-induced correlated trading. As shown in Greenwood & Thesmar (2011), a direct measure should aggregate the *net* demand of the stock from different ETFs. Unfortunately, while we can infer the size of trading on stock $i$ induced by arbitrage activity on ETF $j$, we do not observe the *direction* of trading (whether stock $i$ is bought or sold). As such, we are aggregating the *absolute* demand of the stock from different ETFs rather than the *net* demand. In other words, we acknowledge the measurement errors contained in our proxies which should prevent us from finding significant results in our regressions. To the best of our knowledge, these measurement errors should not be correlated with beta to induce any bias in our exercise. As in the fund-level regressions, we also multiply *Wtd SD* and *Wtd turnover* by *ETF%* in our regressions to capture the idea that a stock is more prone to comovement when it is held more by ETFs and when those ETFs induce more trading.

Although we will use stock and time fixed effects, some time-varying firm-level control variables are also included in the regressions. Summary statistics for these variables appear in Panel B of Table 1. We include the average daily turnover of the stock, which is its volume from CRSP (*vol*) divided by its shares outstanding *(shrout*1,000)*. We also include the log of the stock's market capitalization from CRSP and its book/market ratio (*B/M*) ratio, where the denominator is the market capitalization and the numerator is the latest reported book value from Compustat. *S&P 500*, *DJI* and *Nasdaq 100* are indicators for whether the stock is currently in the S&P 500, Dow Jones Industrials, and Nasdaq 100 indices in that month. These are the three indices with futures trading and the dummy variables control for futures-arbitrage-driven comovement. *Stock turnover* is the stock's average daily turnover during the month. *Index%*, *MF%* and *Ins%* are total index fund holdings, mutual fund holdings and total institutional holdings in percentages, respectively. Mutual fund and index holdings are computed using the CRSP mutual fund holdings database, and institutional holdings are computed using the Thomson database of quarterly holdings. Since ETFs and index funds are mutual funds, their holdings are subtracted from total mutual fund holdings. Institutional holdings are computed using all categories of institutions in the Thomson institutional database and subtracting total CRSP mutual fund holdings, index fund and ETF holdings. The most recent holdings prior to the end of the current quarter are used. In contrast, we use ETF holdings reported as of the end of the latest month to mitigate endogeneity concerns.

### 3.3.2 | Regression results

Table 5 presents regressions at the stock and month level of measures of how the stock covaries with the market on measures of ETF holdings and activity. Both time and stock fixed effects are included. We do not include the control for time trend here since there cannot be a trend in the average CAPM beta which should be close to 1 by construction. Driscoll-Kraay standard errors appear in these tables since these are more conservative than double-clustered standard errors. Columns (1) to (3) show that all three explanatory variables are related to both measures of comovement. A 1% increase in ETF holdings of a stock is associated with a 0.0293 increase in its CAPM beta. This is not a large increase compared to $\beta_M$'s mean value of 1.17 and standard deviation of 0.753, but if ETFs become comparable in size to mutual funds, which have around 20% ownership of many stocks, the associated increase in $\beta_M$ could be much larger.

*Wtd SD* is significant on its own with fixed effects and controls (column (2)), but when it is with the other two explanatory variables of interest, its sign changes (column (4)). This mirrors the weaker performance of this variable in the fund-level tests in the prior section. Therefore, we do not consider it as reliable a driver of correlation as *ETF%* or *Wtd turnover*.

*Wtd turnover* is significantly positively related to beta regardless of the other variables in the model (columns (3) and (4)). Column (3) shows that a one-standard-deviation increase in *Wtd turnover* is associated with a 0.835*0.103 = .09 increase in $\beta_M$. Columns (5) to (6) suggest that *Wtd SD* and *Wtd turnover* interacted with *ETF%* are significant.

The increase in beta of 0.09 is similar in magnitude to the index addition effect, or the increase in beta when a stock is added to the S&P500 index. From a portfolio manager's point of view, a 0.09 increase in her portfolio beta means that she needs to increase her portfolio return by 90 basis points in order to generate the same alpha. As such, the economic consequences of ETF-arbitrage-induced return comovement can be substantial.

### 3.3.3 | Sub-sample cuts

Table 6 shows Table 5's results broken down by terciles of size and turnover. Only the coefficients on the variables of interest are shown but each regression also contains time and stock fixed effects and all of the control variables in Table 5. These tables show that the results tend to be stronger for the smaller stocks (Size 1). Recall that stocks with prices below US$ 5 or market capitalization below US$ 100 million are excluded, so these are not micro-cap stocks. Panel B shows that the effect is also strongest for stocks with lower turnover. These tests help shine a light on why *Wtd SD*, our proxy for creation and redemption activity, is less related to underlying asset correlations than turnover. This variable is robustly positively related to correlations in the smallest terciles of size and turnover but the effect is weaker in the largest tercile. For smaller and lower turnover stocks, it must be more difficult to locate or sell components during creation and redemption.

Overall, the stock-level regression results in this subsection suggest a clear link between a stock's exposure to ETF activity, ETF trading in particular, and its comovement with the market.

**TABLE 5** Stock-level tests

This table presents month/stock panel regressions relating measures of a stock's exposure to ETF activities to two measures of its comovement with the market portfolio. $\beta_M$ is the coefficient of the stock's daily excess returns on daily market excess returns in that month. *ETF %* is the proportion of the stock that is held by ETFs, using CRSP data, on the last day of the prior month. *Wtd SD* is the weighted average percentage standard deviation in the shares outstanding of the ETFs that hold the stock. *Wtd turnover* is the weighted average turnover of the ETFs that hold the stock. Additional control variables and fixed effects are included. *Stock turnover* is the average daily turnover of the stock over the month *Log(Mkt cap)* is the log of the firm's market capitalization. *B/M* is the book-to-market ratio. *S&P500*, *DJI* and *Nasdaq 100* are indicators for whether the stock is currently in the S&P500, Dow Jones Industrials, and Nasdaq 100 indices. *MF %* and *Ins %* is the proportion of the stock held by mutual funds and other institutions, respectively, in percent. *N ETF holders* is the number of ETFs that hold the stock. Detailed variable definitions are given in Appendix A.
We follow Driscoll & Kraay (1998) heteroskedasticity- and autocorrelation-consistent standard errors that are robust to general forms of spatial and temporal dependence appear in parentheses. ***, ** and * signify statistical significance at the 1%, 5% and 10% levels. $R^2$ excludes the explanatory power of fixed effects.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | | | $Y = \beta_M$ | | | |
| *ETF %* | 0.0293*** | | | 0.0214*** | | | 0.00444 |
| | (0.00723) | | | (0.00618) | | | (0.00623) |
| *Wtd SD* | | 1.789*** | | −0.454 | | | |
| | | (0.448) | | (0.422) | | | |
| *Wtd turn* | | | 0.835*** | 0.859*** | | | |
| | | | (0.145) | (0.131) | | | |
| *ETF % *Wtd SD* | | | | | 0.969*** | | 0.121 |
| | | | | | (0.168) | | (0.201) |
| *ETF %* Wtd turn* | | | | | | 0.303*** | 0.268*** |
| | | | | | | (0.0562) | (0.0606) |
| *Stock turn* | 2.934*** | 2.962*** | 2.804*** | 2.744*** | 2.756*** | 2.569*** | 2.574*** |
| | (0.778) | (0.787) | (0.780) | (0.780) | (0.789) | (0.794) | (0.794) |
| *Log(Mkt cap)* | −0.130*** | −0.124*** | −0.122*** | −0.125*** | −0.125*** | −0.121*** | −0.121*** |
| | (0.0318) | (0.0319) | (0.0320) | (0.0320) | (0.0318) | (0.0321) | (0.0320) |
| *B/M* | 0.00675 | 0.00965 | 0.0121 | 0.0108 | 0.00835 | 0.00911 | 0.00881 |
| | (0.00836) | (0.00831) | (0.00829) | (0.00830) | (0.00833) | (0.00839) | (0.00836) |
| *S&P500* | 0.0435* | −0.00328 | −0.0425* | −0.0174 | 0.0100 | −0.0142 | −0.00670 |
| | (0.0234) | (0.0234) | (0.0235) | (0.0238) | (0.0229) | (0.0240) | (0.0238) |
| *DJI* | 0.00971 | 0.0160 | 0.0377 | 0.0297 | 0.0101 | 0.0124 | 0.00985 |
| | (0.0472) | (0.0477) | (0.0478) | (0.0465) | (0.0481) | (0.0467) | (0.0463) |
| *Nasdaq* | 0.0754*** | 0.0885*** | 0.0792*** | 0.0689*** | 0.0816*** | 0.0627*** | 0.0627*** |

(Continues)

**TABLE 5** (Continued)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | | | $Y = \beta_M$ | | | |
| *100* | | | | | | | |
| | (0.0194) | (0.0195) | (0.0194) | (0.0191) | (0.0192) | (0.0187) | (0.0187) |
| *Index %* | −0.0208** | −0.00485 | −0.00154 | −0.0120 | −0.0107 | −0.0117 | −0.0137 |
| | (0.00944) | (0.0104) | (0.00998) | (0.00904) | (0.0104) | (0.0100) | (0.00995) |
| *MF %* | 0.00580*** | 0.00516*** | 0.00499*** | 0.00540*** | 0.00512*** | 0.00502*** | 0.00511*** |
| | (0.000672) | (0.000635) | (0.000600) | (0.000621) | (0.000652) | (0.000666) | (0.000651) |
| *Ins. %* | 0.00345*** | 0.00321*** | 0.00286*** | 0.00298*** | 0.00301*** | 0.00285*** | 0.00289*** |
| | (0.000545) | (0.000561) | (0.000572) | (0.000564) | (0.000602) | (0.000636) | (0.000633) |
| Time FE | YES | YES | YES | YES | YES | YES | YES |
| Stock FE | YES | YES | YES | YES | YES | YES | YES |
| *N* | 232,949 | 232,949 | 232,949 | 232,949 | 232,949 | 232,949 | 232,949 |
| $R^2$ | 0.0582 | 0.0582 | 0.064 | 0.0618 | 0.0597 | 0.0618 | 0.0618 |

# 4 | IS THE RETURN COMOVEMENT EXCESSIVE?

If ETF activity is positively related to return comovement, a natural question follows: does the increased return comovement reflect faster incorporation of common information in the market that ETF trading helps to facilitate; or does it also contain ‘excessive’ price movement due to non-fundamental shocks that ETF trading helps to propagate? Our early analysis using S&P index ETFs suggests that the price co-movement can be ‘excessive.’ We now provide broader evidence at both the fund-level and the stock-level. The key intuition is that if price movement reflects correlated price pressure rather than fundamental information, to the extent that the price pressure is temporary, we should observe subsequent price reversals on both the ETF and the individual stock.

## 4.1 | Fund-level test: autocorrelations

If ETF prices indeed may contain price pressure that subsequently gets propagated to the underlying basket, we would first expect to see reversals in the ETF prices. As a measure of price reversal, we compute the daily autocorrelation of ETF returns for each ETF in our sample in each month.

Figure 2 plots the distributions of these autocorrelations. We first compute the cross-sectional average of the AR(1) coefficients for each month in our sample period. The top figure presents the distribution of these 90 cross-sectional averages. We find a significantly negative mean of −0.06 with a *t*-value of −4.11. The average autocorrelation is negative in 59 out of the 90 months in our sample. We then compute the time-series average of the AR(1) coefficient for each ETF in our sample. The bottom figure presents the distribution of these 549 time-series averages. The average autocorrelation is negative for 488 out of the 549 ETFs. The mean is again −0.06 with a *t*-value of −19.37. Overall, the evidence suggests that ETF prices are strongly negatively correlated at daily frequency, consistent with the existence of noise. Results are similar if we winsorize autocorrelation coefficients at the 1% level to mitigate any effect of outliers.

In Table 7, we also document a significant negative correlation between ETF turnover and the AR(1) coefficient after controlling for other variables such as the size of the ETF and time and fund

**TABLE 6** Stock-level tests: Subsets by size and turnover

This table presents coefficients from stock-month panel regressions of measures of a stock's comovement with the market portfolio on measures of the activity of ETFs holding the stock. The sample period is July 2006 to December 2013. $\beta_M$ is the coefficient of the stock's daily excess returns on daily market excess returns in that month. *ETF %* is the proportion of the stock that is held by ETFs, using CRSP data, on the last day of the prior month. *Wtd SD* is the weighted average percentage standard deviation in the shares outstanding of the ETFs that hold the stock. *Wtd turnover* is the weighted average turnover of the ETFs that hold the stock. All regressions also contain all control variables in Table 5 (*Stock turnover*, *Log(Market cap)*, *B/M*, *S&P 500*, *DJI*, and *Nasdaq 100*, *MF %*, *Ins %* and time and stock fixed effects). Detailed variable definitions appear are given in Appendix A.

Panel A breaks the sample into stock market capitalization terciles where tercile 1 is the smallest. Panel B breaks the sample into terciles by turnover, which is calculated as volume divided by shares outstanding from CRSP. Driscoll & Kraay (1998) heteroskedasticity- and autocorrelation-consistent standard errors that are robust to general forms of spatial and temporal dependence appear in parentheses. ***, ** and * signify statistical significance at the 1%, 5% and 10% levels. $R^2$ excludes the explanatory power of fixed effects.

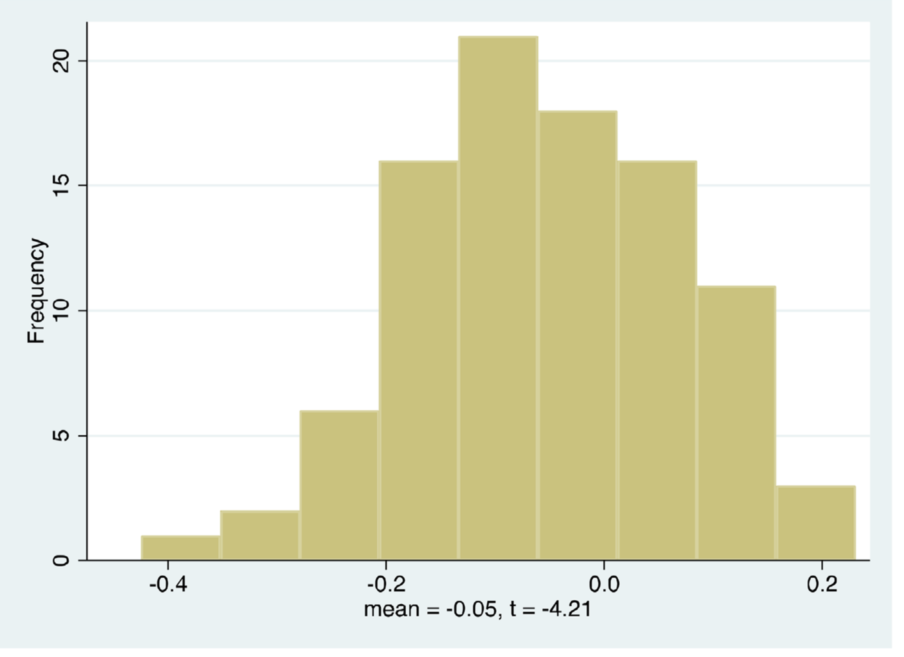
| **Panel A: Size-sorted subsamples** | | | |
|---|---|---|---|
| **Y = $\beta_M$** | **Size 1** | **Size 2** | **Size 3** |
| *ETF %* | 0.0759*** | 0.0219*** | 0.0120*** |
| | (0.0117) | (0.00521) | (0.00394) |
| *Wtd SD* | 2.500*** | 0.948*** | 1.154* |
| | (0.600) | (0.316) | (0.603) |
| *Wtd turnover* | 1.357*** | 0.368*** | 0.570*** |
| | (0.179) | (0.0866) | (0.150) |
| **Panel B: Turnover-sorted subsamples** | | | |
| **Y = $\beta_M$** | **Turn 1** | **Turn 2** | **Turn 3** |
| *ETF %* | 0.0429*** | 0.0117** | 0.0187*** |
| | (0.0161) | (0.00494) | (0.00686) |
| *Wtd SD* | 2.515*** | 0.917** | 0.294 |
| | (0.642) | (0.412) | (0.451) |
| *Wtd turnover* | 1.441*** | 0.366*** | 0.281** |
| | (0.212) | (0.114) | (0.107) |

fixed effect. This negative correlation is consistent with the notion that the noise in ETF could trigger ETF arbitrage and subsequent price reversal. We do not see a significant relationship between ETF turnover and the AR(2) coefficient, suggesting that the price reversal occurs relatively fast and does not usually go beyond a day.

## 4.2 | Stock-level test: lagged betas

If ETF arbitrage propagates price pressure to a large cross-section of individual stocks in its underlying portfolio, we would expect to see ‘excessive’ comovement, or correlated initial price movements that will be reversed subsequently. We examine this effect using a stock's lagged market betas. If an individual stock return on day $t$ contains a component that reflects ‘excessive’ comovement, such a component is likely to revert in the next two days. As a result of this reversal, stock returns on day $t+1$

Distributions of CS average ARs




Distributions of TS average ARs

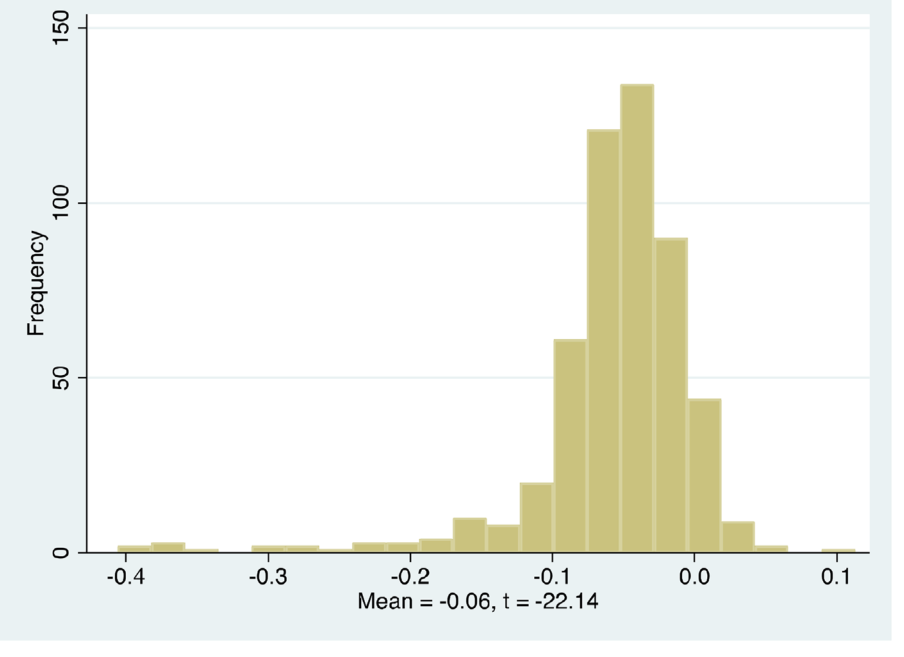



**FIGURE 2** **Distributions of ETF autocorrelation (AR) coefficients.** For each ETF each month, we compute its first-order autocorrelation (AR) using daily returns. We winsorize all autocorrelation coefficients at the 1% level to mitigate the effect of outliers. Each month, we compute the average AR across ETFs. The top figure presents the distributions of these cross-sectional average ARs (for the 90 months in our sample). We also compute the time-series average AR for each ETF. The bottom figure presents the distribution of these time-series averages (for the 549 ETFs in our sample).

**TABLE 7** Daily autocorrelations of ETF returns and ETF activities

This table presents daily autocorrelations of ETF returns and ETF activities. For each ETF each month, we compute its first- and second-order autocorrelations (*AR*(1) and *AR*(2)) using daily returns. We winsorize all autocorrelation coefficients at the 1% level to mitigate the effect of outliers. We then run fund / month panel regressions of these autocorrelations on measures of ETF activities with control variables and fixed effects. *Holdings %* is the proportion of the portfolio's total market capitalization that is owned by the ETF on the last day of the prior month. *SD shares* is the standard deviation of ETF shares outstanding. *ETF turnover* is the average daily turnover of ETF shares. *Expense ratio* is the annual expense ratio of the fund, in percent. *TNA* is total net assets of the fund as of the latest report, in millions of dollars. *Log(N holdings)* is the log of the number of the ETF's holdings of common stock that are also in our CRSP stock sample. Detailed variable definitions are given in Appendix A.
We follow Driscoll & Kraay (1998) to compute a non-parametric covariance matrix estimator that produces heteroskedasticity- and autocorrelation-consistent standard errors that are robust to general forms of spatial and temporal dependence.***, ** and * signify statistical significance at the 1%, 5% and 10% levels.

| | (1) | (2) |
|---|---|---|
| | ***AR*(1)** | ***AR*(2)** |
| *Holdings %* | 0.0215 | −0.00544 |
| | (0.0181) | (0.0152) |
| *SD shares* | −0.0128 | 0.000477 |
| | (0.0476) | (0.0393) |
| *ETF turnover* | −0.0715* | −0.00503 |
| | (0.0384) | (0.0283) |
| *Expense ratio* | 12.72** | 4.431* |
| | (6.347) | (2.660) |
| *Log(TNA)* | −0.00262 | 0.00219 |
| | (0.00438) | (0.00390) |
| *Log(N holdings)* | −0.00545 | 0.000318 |
| | (0.00741) | (0.00487) |
| Time FE | YES | YES |
| Fund FE | YES | YES |
| $N$ | 23,809 | 23,809 |
| $R^2$ | 0.0634 | 0.0381 |

and $t+2$ will likely load negatively on the market return on day $t$. In other words, the stock will have negative lagged market betas. In contrast, if higher return comovement comes from faster incorporation of common information, we should not observe return reversals and hence lagged betas should never be negative. Appendix B demonstrates this point using a simple statistical model of daily stock returns.

For each stock during our sample period and in each month, we compute betas of stock returns on contemporaneous and lagged daily market returns, as follows:

$$R_{i,t} = \sum_{l=0}^{4} \beta_{R_M,i,l} R_{M,t-l} + \varepsilon_{i,t} \tag{12}$$

where $R_{M,t}$ is the return on the market portfolio and $R_{i,t}$ is the daily return on stock $i$, and $l$ is the lag. Note that contemporaneous market returns are included by $l=0$. Table 8, Panel A examines means of

**TABLE 8** Excessive comovement: Evidence from lagged betas

This table presents evidence of excessive comovement. Monthly lagged Betas come from the monthly stock-by-stock regression $R_t = \beta R_t^M + \beta_{R_{t-1}^M} R_{t-1}^M + \beta_{R_{t-2}^M} R_{t-2}^M + \beta_{R_{t-3}^M} R_{t-3}^M + \beta_{R_{t-4}^M} R_{t-4}^M + \varepsilon_t$ where $R_t^M$ is the return on the market portfolio and $R_t$ is the daily return on the stock.

Panel A reports the mean lagged betas for terciles constructed each month by sorting on measures of the stock's exposure to ETF activities. *ETF %* is the proportion of the stock that is held by ETFs, using CRSP data, on the last day of the prior month. *Wtd SD* is the weighted average percentage standard deviation in the shares outstanding of the ETFs that hold the stock. *Wtd turnover* is the weighted average turnover of the ETFs that hold the stock.

Panel B reports panel regression results. *Stock turnover* is the average daily turnover of the stock over the month. *Log(Mkt cap)* is the log of the firm's market capitalization. *B/M* is the book-to-market ratio. *S&P500* is an indicator variable for whether the stock is currently in the S&P500 index. *MF %* and *Ins.%* is the proportion of the stock held by mutual funds and other institutions, respectively, in percent. Columns (1) and (2) correspond to month / stock panel regressions involving lagged betas. Detailed variable definitions appear in the Appendix A. Driscoll & Kraay (1998) heteroskedasticity- and autocorrelation-consistent standard errors that are robust to general forms of spatial and temporal dependence appear in parentheses. ***, ** and * signify statistical significance at the 1%, 5% and 10% levels. $R^2$ excludes the explanatory power of fixed effects.

| **Panel A: Tercile sorts** | | |
|---|---|---|
| | $\beta_{R_{t-1}^M}$ | $\beta_{R_{t-2}^M}$ |
| *Terciles by ETF %* | | |
| 1 | 0.01578 | 0.0046 |
| | (0.01) | (0.81) |
| 3 | −0.0209 | −0.0023 |
| | (0.01) | (0.73) |
| Difference | 0.0366*** | 0.0069 |
| | (0.00) | (0.31) |
| *Terciles by Wtd SD* | | |
| 1 | 0.0376*** | -0.0001 |
| | (0.00) | (0.99) |
| 3 | −0.0344** | −0.0038 |
| | (0.01) | (0.76) |
| Difference | 0.0720*** | 0.0038 |
| | (0.00) | (0.71) |
| *Terciles by Wtd turn* | | |
| 1 | 0.0587*** | 0.0022 |
| | (0.00) | (0.77) |
| 3 | −0.0604*** | −0.0045 |
| | (0.00) | (0.73) |
| Difference | 0.119*** | −0.0045 |
| | (0.00) | (0.48) |

| **Panel B: Panel regressions** | | |
|---|---|---|
| | **(1)** | **(2)** |
| | $\beta_{R_{t-1}^M}$ | $\beta_{R_{t-2}^M}$ |
| *ETF %* | −0.00525** | −0.000478 |
| | (0.00217) | (0.00269) |

(Continues)

**TABLE 8** (Continued)

| Panel B: Panel regressions | | |
|---|---|---|
| | **(1)** | **(2)** |
| | $\beta_{R^M_{t-1}}$ | $\beta_{R^M_{t-2}}$ |
| *Wtd SD* | −0.0926 | −0.272 |
| | (0.375) | (0.200) |
| *Wtd turn* | −0.375*** | −0.136*** |
| | (0.0728) | (0.0474) |
| *Stock turn* | 3.708*** | 0.870 |
| | (0.817) | (0.744) |
| *Log(Mkt cap)* | −0.0481*** | −0.0456*** |
| | (0.0146) | (0.0151) |
| *B/M* | 0.00980 | 0.00276 |
| | (0.00648) | (0.00332) |
| *S&P500* | −0.0156 | 0.0407* |
| | (0.0193) | (0.0209) |
| *MF %* | −0.000530 | −0.000176 |
| | (0.000415) | (0.000403) |
| *Ins. %* | −0.000631** | 0.000127 |
| | (0.000252) | (0.000235) |
| Time FE | YES | YES |
| Stock FE | YES | YES |
| *N* | 227,905 | 227,905 |
| $R^2$ | 0.0299 | 0.0299 |

these betas by tercile of measures of ETF activity, and compares the third (highest) tercile of ETF activity to the first (lowest) tercile of ETF activity. Panel A shows that the lowest tercile of ETF activity tends to have postive betas on lagged market returns, while stocks in the highest tercile of ETF activity tend to have negative betas on lagged market returns. This suggests that stocks in the lowest tercile of ETF activity tend to experience slow incorporation of common information, while stocks in the highest tercile suffer from price overshoot and show reversals, suggesting 'excess' comovement. As in the prior tables of the paper, the results for *Wtd turn* are the strongest. The results are strongest for lags 1 and 2. They are not significant for lags 3 and 4 of market returns and those results remain untabulated.

This effect is confirmed in Panel B, in a regression controlling for other potential determinants of the betas on lagged market returns. This regression shows that measures of ETF activity are negatively related to betas on lagged market returns. As in Panel A, the results are strongest for *Wtd turn*.

To conclude, the results in this section provide strong evidence for price reversals in both ETF and individual stock prices at daily frequency. Such a reversal suggests that at least part of return comovement documented in our paper reflects correlated price pressure, probably caused by ETF arbitrage.[14]

[14]As a specific example of a non-fundamental shock, we examine market-wide investor sentiment as measured by the change in the monthly Baker & Wurgler (2006) investor sentiment index. The preliminary evidence reported in the online Appendix suggests that a one-standard-deviation increase in the weighted average ETF turnover measure is associated with an increase in a stock's sentiment beta that is more than half its mean and almost 10% of its standard deviation.

# 5 | CONCLUSION

We provide empirical evidence that the arbitrage activity between an exchange-traded fund (ETF) and its underlying portfolio could propagate non-fundamental shocks from the ETFs to a broad cross-section of stocks they hold. In other words, ETF arbitrage could be a new source of return comovement.

We first perform an ETF-level analysis and find that an ETF's turnover is an important determinant of the comovement of the stocks in its portfolio. This result holds controlling for time trend, various fixed effects and a host of fund-level control variables. In addition, the more an ETF owns of the market capitalization of its underlying portfolio, the more the stocks in that portfolio tend to move together. This relationship, however, becomes insignificant after controlling for fund and time fixed effects and a host of control variables. Finally, the standard deviation of the ETF's daily shares outstanding, capturing creation and redemption activity, is less strongly related to comovement. The link between ETF activities and return comovement is confirmed in additional tests that exploit the discontinuity in index membership between two S&P stock indices.

We then perform a stock-level analysis. As in the fund-level analysis, we also find that the weighted average turnover of the ETFs that own the stock is related to how much the stock comoves with the market. We find little evidence that weighted average creation and redemption activity of the ETFs that hold the stock is related to the stock's comovement with the market.

Finally, we find evidence suggesting that some ETF-driven return comovement could be excessive, as reflected by subsequent price reversals at both the fund level and the stock level. At the fund level, we find that the ETF's daily returns are negatively autocorrelated and such an autocorrelation is more negative when the ETF turnover is higher. These findings support the notion that ETF prices may at times contain non-fundamental shocks such as price pressure that triggers ETF arbitrage. At the stock-level, we find that stocks with higher measures of ETF activity tend to have significantly negative betas on lagged market returns, and that a stock's lagged betas on market returns are negatively related to the activity of ETFs owning the stock. This suggests that ETF activity is related to overshooting and reversals in prices, a symptom of ‘excess” comovement. In contrast, if ETFs only speed up incorporation of common information, the lagged betas should not be negative.

There is no doubt that the ETF structure provides great benefits. Among others, ETFs provide a cheaper and more efficient way for investors to diversify into a broad asset portfolio. At the same time, the results in our paper suggest that they may also lead to ‘excessive’ comovement among these assets. Such ‘excessive’ price comovement could impose costs to institutional investors who trade often and the costs could even be passed on to many passive individual investors who invest through the institutional investors.

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## SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

**Table A1:** Stock "super-portfolio" beta

**Table A2:** Stock-level tests excluding ETFs holdings less than 100 stocks

**Table A3:** Stock sentiment beta

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# APPENDIX A

## Variable Definitions

| Variable | Definition |
|---|---|
| **ETF-level measures** | |
| *ETF turnover* | Average daily turnover of ETF shares. Turnover is volume (CRSP vol) divided by shares outstanding from Morningstar. CRSP shares outstanding is used if Morningstar shares outstanding is missing. |
| *Expense ratio* | Expense ratio of the fund, from CRSP mutual fund database, in percent. |
| *Fratio* | The ratio of the variance of the portfolio to the average of the variances of the stocks in the portfolio. The ratio is winsorized at the 1% level. |
| *Holdings %* | The proportion of the portfolio's total market capitalization that is owned by the ETF on the last day of the prior month. Holdings are computed using the CRSP Survivor-Bias-Free Mutual fund holdings database. |
| *Log (N holdings)* | The log of the number of holdings of common stock reported to CRSP Mutual fund database and matched to CRSP stock database, that have prices above US$ 5 and market capitalizations above US$ 100,000,000. |
| *SD shares* | The standard deviation of ETF shares outstanding, from Morningstar. CRSP shares outstanding is used if Morningstar shares outstanding is missing. |
| *TNA* | Total net assets of the fund as of the latest report, from the CRSP Mutual Fund Database, in millions of dollars. |
| **Stock-level measures** | |
| $\beta_M$ | Coefficient of the stock's daily excess returns on daily market excess returns in that month. |
| $\beta_{SENT}$ | Regression coefficient on $\Delta SENT$ from regressing monthly stock excess returns on monthly market excess returns and $\Delta SENT$ where $\Delta SENT$ denotes the orthogonalized change in monthly Baker & Wurgler (2006) sentiment index. |
| *B/M* | Book-to-market ratio. Book values are from Compustat and market value is log(abs(prc) *shrout*1000) from CRSP. Negative book values are set to missing. |
| *ETF %* | Proportion of the stock that is held by ETFs, using CRSP mutual fund holdings data and market capitalization data, on the last day of the prior month. |
| *Ins. %* | Percentage of the stock that is held by any institution in the Thomson database minus the proportion that is held by CRSP mutual funds. |
| *Log(Mkt cap)* | The log of the firm's market capitalization, *log*(*abs*(*prc*)* *shrout** 1000), from CRSP. |
| *MF %* | Percentage of the stock that is held by CRSP mutual funds minus the proportion that is held by ETFs. |
| *N ETF holders* | The number of ETFs holding the stock. |
| *S&P500* | Indicator for whether the stock is a S&P500 member in that month. |
| *Stock turnover* | Average daily turnover over the month from CRSP. Turnover is *vol*/(*shrout**1000). |

(Continues)

**(Continued)**

| Variable | Definition |
|---|---|
| *Wtd SD* | Weighted average percentage standard deviation in the shares outstanding of the ETFs that hold the stock. The weights are proportional to the holdings of each ETF that holds the stock. |
| *Wtd turnover* | Weighted average turnover of the ETFs that hold the stock. The weights are proportional to the holdings of each ETF that holds the stock. |

## APPENDIX B

### Lagged Beta

Assume the log stock market index at the end of day $t$ contains a price pressure component, $\varepsilon_t$, generated by correlated trading in an ETF arbitrage as a large portfolio of stocks are bought and sold simultaneously. The price pressure on different stocks tends to be in the same direction and thus will not cancel out at the market level. $\varepsilon_t$ is assumed to follow an AR(1) process:

$$\varepsilon_t = \rho\varepsilon_{t-1} + \eta_t, 0 < \rho < 1.$$

A small $\rho$ indices a transitory price pressure. The observed log market daily excess return (ignoring dividends) is:

$$\tilde{r}_{M,t} = r_{M,t} + \Delta\varepsilon_t,$$

where $r_{M,t}$ denotes daily market excess return due to fundamental information. The observed log individual stock excess return can be modelled as:

$$\tilde{r}_{i,t} = (1-\phi_i)\beta_i r_{M,t} + \phi_i\beta_i r_{M,t-1} + \lambda_i\Delta\varepsilon_t + \xi_t,$$

where 1> $\phi_i > 0$ captures slow incorporation of market-wide information and $\lambda_i > 0$ captures the impact of the market-wide price pressure on stock $i$. We expect $\lambda_i$ to be higher for stocks with more exposure to ETF activities.

The lagged beta with 1-day lag can be computed as the slope coefficient from regressing $\tilde{r}_{i,t}$ on $\tilde{r}_{M,t-1}$, or

$$\beta_{R_M,i,1} \propto \mathrm{Cov}\left(\tilde{r}_{i,t}, \tilde{r}_{M,t}\right) = \phi_i\beta_i Var(r_M) + \lambda_i(\rho-1)Var(\varepsilon).$$

The first term comes from slow incorporation of market information and is positive. The second term comes from correlated price pressure and is negative. This is because the transitory price pressure generates reversals in daily returns on both the market and the individual stock. A negative lagged beta therefore confirms the presence of correlated price pressure.