Using ETFs to conceal insider trading*

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Abstract

We show that exchange traded funds (ETFs) are used in a new form of insider trading known as "shadow trading." Our evidence suggests that some traders in possession of material non-public information about upcoming M&A announcements trade in ETFs that contain the target stock, rather than trading the underlying company shares, thereby concealing their insider trading. Using bootstrap techniques to identify abnormal trading in treatment and control samples, we find significant levels of shadow trading in 3-6% of same-industry ETFs prior to M&A announcements, equating to at least $212 million of such trading per annum. Our findings suggest insider trading is more pervasive than just the "direct" forms that have been the focus of research and enforcement to date.

Keywords: insider trading, shadow trading, ETF, stock

JEL classification: G14, G23

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1. Introduction

In recent times, traders have implemented new strategies to circumvent detection by law enforcement agencies for illegal insider trading. These involve trading in related securities. For example, in the only prosecution case of its kind to date, in August 2021, the SEC charged a former employee of Medivation (MDVN, a biopharmaceutical company) for insider trading prior to Pfizer's (PFE) acquisition of MDVN (SEC, 2021). Prior to the acquisition announcement in 2016, the employee purchased options in Incyte (INCY, a similar sized biopharmaceutical company). On the merger and acquisitions (M&A) announcement date, INCY's stock price increased by 8%, and the MDVN employee generated profits of $107,066. The MDVN employee was charged for breaching MDVN's trading policy, by using material non-public information to trade in a related stock (i.e., INCY). Insider trading of this type, involving trading in economically related firms (e.g., business partners or competitors), is termed "shadow trading" by Mehta et al. (2020).[1]

In this paper, we expose and quantify a new type of shadow trading using exchange-traded funds (ETF). ETFs provide an attractive instrument for insiders to trade their private information for several reasons. First, the stock that is the subject of the information may be a constituent of the ETF, so that one can get a direct exposure to the company's share price via the ETF, but in a vehicle that is more subtle than trading the company shares directly, helping reduce scrutiny from law enforcement. Second, ETFs are cost-effective and often more liquid than the underlying company shares (e.g., Buckle et al., 2018), potentially reducing the price impact of insider trades. Both theoretical and empirical evidence shows that insiders trade in highly liquid assets so that they can hide their information and maximize their trading profits (e.g., Lei and Wang, 2014; Ben-David et al., 2018). Third, shadow trading in ETFs prior to price-sensitive news allows insiders to benefit from increases in the price of both the source firm and related firms.

For the material information events, we analyze M&A announcements as they provide the cleanest setting for examining shadow trading in ETFs. First, M&As have significant impacts on stock prices, creating strong incentives for illegal insider trading (e.g., Huang and Walking, 1987; Masulis and Simsir, 2018; Lee, 2020). For example, Patel and Putniņš (2022) estimate that direct illegal insider trading in stocks occurs prior to 20% of M&As. Second, M&As are one of the most frequent of the major, unscheduled price sensitive announcements made by companies, which improves the power of our tests. We do not consider scheduled information events because anticipation effects and hedging activities around those events can be difficult to distinguish from the abnormal trading that is due to insider trading.

[1] While both shadow trading and traditional illegal insider trading are based on private information about a firm, the former involves trading shares in a related firm and the latter involves trading shares in the firm directly.

Using a 13-year sample period (2009 to 2021) of all US companies and ETFs, we find evidence of widespread shadow trading in ETFs prior to price-sensitive news. Using a percentile test, we observe statistically significant increases in ETF volume in the five-day period prior to M&A news in 3-6% of same-industry ETFs on average. These ETFs, which are the most likely to be traded by insiders if shadow trading does occur, have significantly higher levels of abnormal trading than various randomized control samples of other ETFs and other trading days. We eliminate M&A events that are preceded by rumors to ensure that the analysis is not picking up general information leakage.

Using multivariate OLS regressions, we find that the abnormal pre-announcement ETF volume in the five-day period prior to the M&A announcement date is significantly larger in same-industry ETFs relative to ETFs in the control sample, controlling for a number of further factors. The shadow trading is economically large, with abnormal volume equal to 31% of the full sample standard deviation of abnormal volume.

A challenge in quantifying shadow trading is that purely by statistical chance we will observe some ETFs that have abnormal volume prior to price-sensitive news events. This challenge is similar to the one in the funds management literature that tries to disentangle skill from luck in the cross-section of portfolio managers. Following the funds management literature, we apply a bootstrap approach to overcome these econometric issues and quantify the amount of shadow trading that is beyond what would be observed by statistical chance.

The bootstrap approach that we employ also identifies key characteristics of shadow trading in ETFs. We find that insiders strategically hide their information by trading ETFs (rather than the underlying stocks), but also by trading ETFs with high liquidity (e.g., Admati and Pfleiderer, 1988; Ben-David et al., 2018). Furthermore, shadow trading in ETFs is more likely when the potential profits from the trades are higher, that is, when the stock price impact of information is larger, such as in M&A target firms that have large cumulative abnormal returns, when the target firm represents a larger weight in the ETF portfolio, and when insiders have a greater information advantage over other investors (e.g., in small target firms subject to M&A bids).

The amount of shadow trading identified by our approach is economically meaningful. We estimate that the total dollar volume of such trading is at least $2.75 billion during our sample period, or $212 million on average per annum. Our estimates of the amount of shadow trading in ETFs provide a lower bound given that we only examine shadow trading prior to M&As and not prior to other price-sensitive news announcements.

We find that these results are robust to a large number of alternative specifications and filters. We also conduct falsification tests in which we examine whether abnormal trading is identified by our approach in ETFs where we would not expect shadow trading. These tests support the conclusion that the abnormal trading that we identify in the main analysis is unlikely to be spurious or the result of particular modelling choices.

In terms of time-series trends, we find that shadow trading occurs in 2-5% and 7-14% of ETFs in the first and second halves of the sample period (between 2009-2013 and 2014-2019, respectively). Only between 2014-2019 is abnormal ETF volume in the treatment sample significantly larger than ETFs in the control sample. The increase in shadow trading from 2009-2013 to 2014-2019 is consistent with the increasing popularity and liquidity of ETFs as an investment vehicle, making it more attractive to use ETFs for shadow trading. During the final two years of our sample period, we find little evidence of shadow trading in ETFs consistent with increasing regulatory attention towards shadow trading (e.g., the first SEC shadow trading prosecution occurs in 2021). The dollar amount of shadow trading has similar time series trends, averaging \$150 million and \$360 million per year between 2009-2013 and 2014-2020, respectively.

We find that shadow trading is most prevalent in the Health Care, Technology, and Industrials sectors. For these three industries, shadow trading occurs in 2-12% of ETFs. In addition, more than 80% of the total dollar amount of shadow trading occurs in these three industries. Our findings are consistent with higher amounts of shadow trading in industries where insiders have a greater information advantage over other investors (e.g., firms with higher levels of trade secrecy), the value of information is larger (e.g., larger target firm CARs), and insiders have more choice in terms of ETFs tracking these sectors.

This paper contributes to several areas of the literature. First, Mehta et al. (2020) show that company insiders use private information about their own firm to trade in related firms (e.g., business partners or competitors). We contribute by showing that such shadow trading goes beyond related companies and occurs in economically meaningful scales in ETFs. Recent charges against a MDVN employee for trading their private information in INCY, shows that regulators have started to monitor and enforce against shadow trading in related stocks. Our paper suggests law enforcement agencies should also investigate trading in other related securities such as ETFs.

Second, this paper contributes to the literature that estimates the prevalence of illegal insider trading. Recent evidence from Patel and Putniņš (2022) finds that insider trading in stock markets is pervasive. Using structural estimation techniques, they estimate that illegal insider trading occurs prior to 20% of M&As and 5% of earnings announcements, such estimates are least four times larger than captured by SEC prosecution cases. Using abnormal options volume, Augustin et al. (2019) find insider trading in options markets as well. We take this one step further and show insider trading is even broader and occurs in securities other than the stocks themselves.

Third, several studies examine the characteristics of insider trading. SEC prosecutions reveal that insiders trade on days with very large stock returns, reduce their trading intensity when regulatory enforcement increases, and increase their trading speed if their private information is also known by other insiders (e.g., Meulbroek, 1992; Kacpercyzk and Pagnotta, 2019, 2020). Our paper sheds new light on the characteristics of insider trading strategies using ETFs.

Fourth, the role of ETFs in price discovery is at the center of an unresolved debate. On one hand, ETFs are viewed as purely passive investment vehicles as by construction they track various indices. On the other hand, the growing number and diversity of ETFs and increases in ETF liquidity provide cost-effective vehicles for informed traders to profit from their private information. For example, Bernile et al (2016) report abnormal increases in ETF order imbalance prior to surprises in macroeconomic news (i.e., FOMC interest rate decisions, non-farm payrolls, consumer price index, gross domestic product).[2] Our findings contribute to the debate by showing in a specific context, that informed traders do use ETFs, but with subdued price impacts.

Our results have implications for regulators. The focus of law enforcement agencies to date has been on prosecuting insiders for trading directly in their own (or closely related) companies. Our evidence suggests monitoring of abnormal trading should be broader than just the shares of companies. Furthermore, the Insider Trading Prohibition Act has recently been passed by the House of Representatives, providing a step towards codifying insider trading violations (e.g., Mukhi et al., 2019; Godoy, 2021). Regulators should consider the growing strategies implemented by insiders to avoid being caught (e.g., shadow trading) in their broadening of insider trading regulations.

2. Data

We obtain data for the sample period between January 1, 2009 and December 31, 2021. From *Datastream*, we obtain data on 3,209 M&As of US-based target firms, where at least 50% of the target firm's equity is purchased, and the *Datastream* code and daily information for the target firm is not missing. We also obtain daily stock prices and trading activity, daily Russell 3000 total return index, and monthly stock characteristic data from *Datastream*.

We use the Eikon Search Tool to screen relevant ETFs. Using Lipper and Industry Classification Benchmark (ICB) classifications, we obtain 1,411 sector ETFs (including their RIC codes) which are primary US-based issues. We ensure our sample is not subject to survivorship bias as we include delisted

[2] For studies examining the informational efficiency of ETFs and their underlying basket of securities, see, Xu et al. (2019) and Glosten et al. (2021).

ETFs during the sample period. Using RIC codes, we obtain daily ETF price and trading activity and monthly characteristic data from *Datastream*.

Following Ince and Porter (2006) and Kumar et al. (2021), we apply several return filters to remove data errors and outliers. We set the daily stock returns of both days d and $d-1$ to be missing if $R_{i,d}R_{i,d-1} \leq 50\%$, where $R_{i,d}$ is the gross return of stock i on day d, and at least one of the two returns is 200% or more. To avoid rounding errors, daily stock returns are set to be missing if the return index for the Russell 3000 for either the previous day or the current day is smaller than 0.01. Similar filters are applied to daily ETF returns. In addition, we exclude days from our sample period if more than 90% of stocks on a given exchange have returns equal to 0%, and in each month, we exclude a stock or ETF if the number of zero-return days exceeds 80%. The application of these return filters reduces the sample to 3,150 target firms and 1,207 ETFs. ICB industry codes are used to match target firms to same-industry ETFs, this further reduces the sample to 3,140 target firms. Last, we require non-missing stock returns during the [-1,+1] period around the M&A announcement, resulting in final sample of 2,711 target firms corresponding with 2,734 M&A deals (i.e., 23 stocks are targets for two M&A deals).

< Table 1 here >

Table 1 reports descriptive statistics for the 2,734 M&A deals in our sample. Panel A shows that on average, target firm market capitalization is $1,491 million, the cumulative abnormal return of the target firm during the period [-1,+1] around the M&A announcement date is equal to 20%, and that more than 97% of target firm shares are purchased by the acquirer. Panel B shows that most M&A deals in our sample are mergers (94%), occur in the Financials (25%), Health care (14%), Technology (14%), Consumer discretionary (13%), and Industrials (10%) sectors, and the acquiring firm is US-based (86%).

3. Method

3.1. Shadow trading measures

Following prior studies of insider trading before price-sensitive news, we use several measures to proxy for shadow trading using same-industry ETFs. Meulbroek (1992) and Fishe and Robe (2004) find that abnormal trading volume can be used to identify the presence of insider trading. Similarly, Foley et al. (2021) and Patel and Putniņš (2022) find that pre-announcement abnormal volume and return run-ups significantly predict insider trading in M&A target firms.

Driven by the literature, we test for shadow trading by examining abnormal volume in same-industry ETFs during the [-5,-1] period prior to the M&A announcement date ($Abnormal\ volume_i$):

$$Abnormal\ volume_i = \frac{V_i[-5,-1]-V_i[-30,-11]}{V_i[-5,-1]+V_i[-30,-11]}, \tag{1}$$

where $V_i[-5,-1]$ ($V_i[-30,-11]$) is the average daily volume traded in the same-industry ETF i during the [-5,-1] ([-30,-11]) period prior to the M&A announcement date. Our measure of abnormal volume in Eq. (1) is scaled, so that our measure has the range [-1,+1].

The insider trading literature also sometimes uses price runups ahead of announcements as indications of insider trading. For example, Tang and Xu (2016) find that return run-ups prior to material news can be predicted by illegal insider trading volume. However, we expect that price runups in ETFs would be much smaller than in individual stocks or non-existent in the lead up to material information announcements. This is because ETFs are often more liquid than the underlying stocks, leading to smaller price impacts for a given amount of trading. Further, arbitrage activities tie the ETF price to the basket of stocks that underpin the ETF, making it unlikely that an insider trader would have a material impact on the price of an ETF, even if they traded a significant volume of the ETF.[3] Therefore, we focus on abnormal volumes as they are more likely to reveal the presence of shadow trading in ETFs, if such trading is present.

3.2. Bootstrap approach

A key challenge in analyzing a large sample of ETFs, is that we will observe some abnormal levels of ETF trading activity prior to M&A announcements purely by statistical chance. Our challenge is analogous to that faced by studies separating fund manager skill and luck. In such settings, Type I errors can arise when fund managers beat their benchmarks through luck, even across multiple periods, resulting in incorrect conclusions.

Following the funds management and microstructure literature (e.g., Kosowski et al., 2006; Reeb et al., 2014; Augustin et al., 2019; Putniņš and Barbara, 2020), we use a bootstrap approach to quantify the amount of shadow trading beyond statistical chance. In essence, we compare the distribution of shadow trading measured using *Abnormal volume* between a treatment sample (referred to as the "*suspected*"

[3] For example, given an index where the underlying stocks have a combined market capitalization of $100 million, and an ETF which holds 1% of the same underlying stocks (resulting in an ETF market capitalization of $1 million). If both the stocks and ETF have trade turnover ratios of 1, then the trading volume of stocks and the ETF is $100 million and $1 million, respectively. In the scenario an insider trades $1 million of the ETF, this has doubled the typical ETF volume, thus making such volume detectable, however, such volume is only equivalent to 1/100th of the volume of the underlying stock index which will likely have a negligible impact on the market prices of the index and the ETF, if the two prices are linked by arbitrage.

sample) of ETFs that are the most likely to be used by insiders for shadow trading prior to M&A announcements if such shadow trading occurs, and a control sample created through random sampling.

Driven by the insider trading literature, we create a treatment sample of same-industry ETFs whose constituents include the M&A target firm and other firms operating in the same industry as the target firm. Shadow trading is more likely to occur in liquid securities, where traders can hide their trades among noise traders (e.g., Admati and Pfleiderer, 1988). ETFs are several times more liquid than the underlying stocks, thereby, they provide an attractive setting for insiders to strategically shadow trade (e.g., Subrahmanyam, 1991; Chelley-Steeley and Park, 2010; Marshall et al., 2018). We use market capitalization to proxy for ETF liquidity and therefore require the same-industry ETF market capitalization to exceed the yearly median value.

To increase the power of the tests, we also focus in on the M&A deals for which insider or shadow trading is most likely, otherwise the empirical analysis faces a high level of noise from events that are unlikely to have insider trading. Insider trading is positively correlated with the value of information, that is, when the difference between fundamental value and target stock price is larger, or when private information has a higher expected payoff (e.g., Becker, 1974). We measure the value of information in several dimensions. To be included in the treatment sample, we require the target firm announcement return to exceed the yearly median, the target firm's market capitalization to exceed the yearly median value, and the 180-day rolling correlation of the target firm returns and same-industry ETF returns during the period [-180,-1] prior to the M&A announcement date to be in the top quartile across the full sample of ETFs per deal ($Stock - ETF\ relatedness_i$).[4] In such cases, the probability of shadow trading in ETFs is higher because the value of information is more likely to generate larger returns in the closely-related ETF (i.e., through larger target firm returns or through the target firm having a larger weight in the ETF's underlying portfolio).

Further, we require the M&A deal to be not rumored as such deals are associated with a lower value of information and the presence of rumors could contaminate our tests by creating abnormal trading that is not due to insider trading. Like prior studies (e.g., Alperovych et al., 2021), we find that in our sample of M&As, rumored deals have lower target firm announcement CARs when compared to non-rumored deals (e.g., 9.9% versus 21.8%).

The application of our filters reduces the full sample of 2,734 M&A deals to 341 "suspect" deals which are included in our treatment sample. We relax each of the filters in robustness tests and find that our results still hold. For each of these deals in the treatment sample, we calculate *Abnormal volume* in the ten largest

[4] As we do not have access to ETF holdings data, we proxy for portfolio weight, using the target firm's market capitalization and $Stock - ETF\ relatedness_i$.

same-industry ETFs. Although we suspect that insiders will strategically trade in the largest and most liquid same-industry ETF, we consider up to ten highly-correlated ETFs to account for individual preferences. In cases where there are less than ten same-industry ETFs, we consider the ETFs that meet our filters. After the application of our filters, our treatment sample consists of 2,734 same-industry ETFs in which insiders are likely to undertake shadow trading prior to 341 M&A deals (i.e., 2,734 suspected deal-ETF pairs). In robustness tests, we draw similar conclusions when we vary the filters applied to creating the treatment sample.

For each of the 2,734 suspected deal-ETF pairs within the treatment sample, we create a bootstrapped control sample of 1,000 random observations. The control sample provides a baseline of the variation in abnormal trading that we expect to observe by chance.

We construct three different versions of the control sample using random sampling with replacement:

(i) *Random-dates*, which compares trading in the suspected same-industry ETF immediately prior to the M&A (the suspected shadow trading period) to trading in the same ETF on other (random) dates, where shadow trading is not expected;

(ii) *Random-ETF*, which compares trading in the suspected same-industry ETF immediately prior to the M&A (the suspected shadow trading period) to trading in other (random) ETFs from the control sample on the same dates; and

(iii) *Random-ETF/dates*, which compares trading in the suspected same-industry ETF immediately prior to the M&A (the suspected shadow trading period) to trading in other (random) ETFs from the control sample on other (random) dates.[5]

The use of these different randomized benchmarks for what is deemed a normal or baseline level of trading characteristics adds robustness to the approach, ensuring the results are not driven by a specific cross-sectional or time-series choice as to what is deemed normal.

4. Main results

4.1. Prevalence of shadow trading in ETFs

We use a percentile test to formally compare the distribution of *Abnormal volume* between the treatment and control samples. In this test, we count what proportion of the same-industry ETFs with suspected shadow trading (i.e., treatment sample) have a higher value of *Abnormal volume* than the 50th

[5] To ensure that our control sample is not driven by shadow trading and the market reaction to the M&A news, For the *Random-dates* and *Random-ETF/dates* control distributions, we require the random dates to be at least one-month before and after the M&A announcement date of the target firm. For all three versions of the control sample, we exclude periods when the randomly chosen ETF is suspected to have shadow trading during the [-30,+30] period of another M&A deal.

percentile of random distributions created by sampling with replacement (i.e., control samples). The test is based on the notion that if there is no abnormal trading in the treatment sample, the treatment and control distributions will be approximately the same and so approximately 50% of the ETFs in the treatment sample will have abnormal trading above/below the 50th percentile in the random control distribution. If there is shadow trading that creates abnormal volume in some ETFs in the treatment sample, then these ETFs will result in more than 50% of the ETFs in the treatment sample having abnormal trading above the 50th percentile in the random control distribution.

The intuition for the test is that if there was no shadow trading, then half of the treatment sample should have *Abnormal volume* higher than the 50th percentile in the control sample, as the treatment distribution would be approximately the same as the random control distribution. However, if shadow trading is present in a significant number of the suspected ETFs and it creates increased values of *Abnormal volume* then we will see the median in the treatment sample significantly exceed that of the control sample. Using a t-test to test for statistical significance, if significantly more than 50% of the ETFs in the treatment sample have *Abnormal volume* that significantly exceeds the 50th percentile of the random control distribution, this would provide evidence that a meaningful amount of shadow trading occurs in ETFs prior to M&A announcements. Due to the high liquidity of ETFs, shadow trading in ETFs may not push abnormal volumes into the tails of the distribution, but will nevertheless elevate them, and therefore comparisons of the 50th percentiles of the distributions are more likely to detect shadow trading than comparisons of the tails of the distributions.

< Table 2 here >

Table 2 reports the results from the bootstrapped percentile test. Using abnormal ETF volume, we find that shadow trading occurs prior to M&As in 3-6% of the ETFs in the treatment sample. Using a t-test, our findings are statistically significant at a 99% confidence level. For example, when the control sample is generated using random dates and random ETFs (Random-ETF/dates), we find evidence of shadow trading in 6.18% of ETFs in which insiders are likely to trade (i.e., 56.18% – 50% percentile).[6]

[6] As a robustness test, we repeat the same steps, but we count how many of the same-industry ETFs with suspected shadow trading (i.e., treatment sample) have a higher value than the 60th percentile of random distributions created with sampling with replacement (i.e., control samples). We find that a statistically significant amount of shadow trading occurs in 4-5% of the ETFs in the treatment sample prior to price-sensitive news.

4.2. Abnormal volumes attributable to shadow trading in ETFs

We extend the tests in the previous section to a multivariate framework. Using ETF-target firm-day (i, x, t) observations, we use OLS panel regressions to estimate the scale and determinants of shadow trading in ETFs, while controlling for multiple factors:

$$ShadowTrading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j \, TGTControls_{j,x,t} + \sum_k \gamma_k \, ETFControls_{k,i,t} + \varepsilon_{i,x,t}, \quad (2)$$

where $ShadowTrading_{i,x,t}$ is measured using the abnormal ETF trading volume during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). $Suspected_{i,x,t}$ is equal to one for ETFs with suspected shadow trading prior to M&As (i.e., ETFs in the treatment sample), and zero for ETFs in the control sample (for each observation from the treatment sample, we obtain 20 observations from the Random-ETF/dates bootstrapped control sample).

In the regressions, we control for ETF and target firm control variables including: the market capitalization of the target firm expressed in log form ($TGTMktCap_{x,t}$), the market-to-book value of the target firm's assets ($TGTMB_{x,t}$), the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date ($TGTCAR_{x,t}$), the market capitalization of the ETF expressed in log form ($ETFMktCap_{i,x,t}$), and the average traded volume by the average number of shares of the ETF ($ETFTurnover_{i,x,t}$). We include ETF and month (m) fixed effects.

< Table 3 here >

Table 3 reports the results from the multivariate OLS regressions. The positive and statistically significant $Suspected_{i,x,t}$ coefficient indicates that abnormal volume in the five-day period prior to the M&A announcement date is significantly larger in same-industry ETFs that are more likely to be traded by insiders engaging in shadow trading, relative to the control sample. The results are statistically significant at a 99% confidence level and economically meaningful – the abnormal volume is about 31% of its full sample standard deviation. Overall, the results show the presence of shadow trading in ETFs (proxied by abnormal ETF volume) prior to M&A announcements.

4.3. Shadow trading in ETFs through time

In this section, we examine how shadow trading in ETFs varies through time. To ensure sufficient observations in our tests, we partition the 13-year sample period into two- and three- year sample periods.

Table 4 reports the findings from the percentile test and multivariate OLS regressions. We observe from both the percentile test and OLS regressions, that there is strong evidence of shadow trading in ETFs between 2014 and 2019, and lower levels of shadow trading at the start (i.e., 2009 to 2013) and end (i.e., 2020 to 2021) of our sample period.

< Table 4 here >

Similar to the full sample findings, during the first three years of our sample period (i.e., 2009 to 2011), the percentile test indicates that shadow trading occurs in 2.81-5.95% of same-industry ETFs relative to ETFs in the Random-ETF and Random-ETF/dates control samples. Between 2012 and 2013, shadow trading takes place in approximately 2-4% of ETFs in the treatment sample.

During the 2009 to 2011, and 2012 to 2013 subsamples, the $Suspected_{i,x,t}$ coefficient estimate from our OLS multivariate regression model indicates that abnormal pre-announcement volume for ETFs in the treatment sample is larger than volume in the control sample, but this difference is not statistically significant. The relatively weaker evidence of shadow trading occurring prior to price-sensitive news during the beginning of our 13-year sample period is consistent with ETFs emerging as a popular investment vehicle from 2008 onwards. At this time, assets under management increased significantly, a higher variety of investment options was offered, and economies of scale and competition drove down trading costs and improved liquidity (e.g., Johnson, 2021; Ben-David et al., 2022).

Subsequent to ETFs becoming an established mainstream investment vehicle, we find strong evidence of shadow trading prior to price-sensitive news (2014 to 2019). The percentile tests indicate that shadow trading occurs in 7-19%, 8-11%, and 7-14% of ETFs in the treatment sample between 2014-2015, 2016-2017, and 2018-2019, respectively. The $Suspected_{i,x,t}$ coefficient estimate indicates that *Abnormal volume* in ETFs most likely to be used by insiders is significantly larger than volume in other ETFs between 2014-2019.

During the last two years of our sample period, the results from both the percentile test and the multivariate OLS regression model indicate insignificant differences between ETFs in the treatment and control samples, suggesting less or no shadow trading between 2020 and 2021. We find that the reduced amount of shadow trading is not due to fewer opportunities to shadow trade, as both the potential profits from trading on M&A deals remains similar throughout the sample period (i.e., target firm pre-announcement CARs of 25-30%) and the number of ETFs available to trade continues to grow.

We provide two explanations for this result. The first is that the number of insiders engaged in shadow trading increases, but relative ETF volume increases at a larger rate (e.g., record levels of ETF traded volume were recorded in 2020 and 2021). As a result, the relative share of shadow traders as a proportion of total ETF clientele decreases, resulting in insignificant results in our percentile and multivariate regression tests. Put simply, if ETFs are very liquid and highly traded, shadow trading becomes difficult to detect via abnormal trading measures.

The second explanation is increases in regulatory scrutiny and law enforcement agency attention relating to insider trading and shadow trading. In late 2019, the House of Representatives passed the Insider Trading Prohibition Act (ITPA). The ITPA attempts to codify insider trading court precedents into a statute and ultimately make it easier to prosecute illegal insider trading. Further, in August 2021, the SEC charged a former employee of MDVN for shadow trading in related stocks prior to PFE's acquisition bid.

4.4. Shadow trading in ETFs by industry

We examine the prevalence of shadow trading in ETFs across industries. Table 5 reports the results from the percentile test and OLS multivariate regressions by industry. For the three industries with the highest number of M&A deals in our sample — Health Care, Technology, and Industrials — we find that shadow trading occurs in 3-6%, 6-12%, and 2-4% of ETFs in the treatment sample, respectively. For these three industries, *Abnormal volume* is significantly larger in ETFs more likely to be used by insiders for shadow trading, relative to other ETFs (see $Suspected_{i,x,t}$ coefficient estimate).

Higher shadow trading in these three industries is consistent with insiders having a greater information advantage over other investors due to higher information asymmetry. For example, firms operating in the Health Care or Technology sectors have higher levels of trade secrecy and innovation (e.g., Rahman et al., 2021). Further, insiders are more likely to undertake insider trading when the potential payoff is higher, that is, when the value of information is larger. The average pre-announcement target firm CAR is 28.6% and 23.8% for the Health care and Technology sectors, respectively, which exceeds an average of 20% across all deals. There are also more ETFs tracking these three industries than any other: 132, 75, and 58 ETFs track the Technology, Energy, and Health Care sectors, respectively, relative to an average of 44 ETFs in other industries. This provides insiders with more scope to trade ETFs that suit their shadow trading strategy (e.g., liquidity, cost, exposure to the target stock).

< Table 5 here >

We also find evidence of shadow trading in the Real Estate, Telecommunications, Energy, and Utilities sectors. For the remaining industries, we find mainly insignificant results in the percentile and multivariate regression tests.

4.5. Economic significance of shadow trading in ETFs

To gauge the economic significance of shadow trading in ETFs, we calculate the total dollar value of shadow trading ($\$ShadowTrading$) during our sample period. This estimate is calculated as the difference between the sum of *Abnormal volume* in all ETFs in the treatment sample and the sum of *Abnormal volume* in all ETFs in the control sample divided by 1,000 (as there are 1,000 observations in the control sample for each ETF-target firm-day in the treatment sample).

As we estimate three different versions of the control sample (Random-dates, Random-ETF, and Random-ETF/dates), we calculate three different estimates for $\$ShadowTrading$. For robustness, and to mitigate the effects of outliers, in our calculation of $\$ShadowTrading$ we winsorize *Abnormal volume* using ETF-day observations at the $1^{st}/99^{th}$ and $5^{th}/95^{th}$ percentiles, but acknowledge that by construction this winsorization likely throws away some of the actual shadow trading that creates the largest abnormal volume.

Table 6 reports the matrix of $\$ShadowTrading$ expressed in millions of dollars using different control samples and levels of winsorization. The estimated dollar value of shadow trading during the 13-year sample period ranges from \$2.4 billion (applying winsorization at the $5^{th}/95^{th}$ percentiles) to \$68.1 billion (applying no winsorization). Annual equivalents of these dollar amounts are \$185 million to \$5.2 billion per annum.

< Table 6 here >

To obtain a more precise estimate of the economic magnitude of shadow trading in ETFs, we use back-of-the-envelope calculations to estimate $\$ShadowTrading$ for three of the ETFs that are most frequently used by insiders in our treatment sample: IGV (iShares Expanded Tech-Software Sector ETF), VIS (Vanguard Industrials ETF), and VHT (Vanguard Health care ETF). For IGV, on April 3, 2022, its share price is \$345 and its 50-day average trading volume is 678,264 shares. Using IGV data and our estimates from the percentile tests (3.80-6% of the 2,734 ETFs in our treatment sample are used for shadow trading) and from our OLS regressions, we estimate $\$ShadowTrading$ to range from \$3 billion (i.e., = \$345 × 678,264 shares × 5 days × 3.80% × 2.50% × 2,734 ETFs) to \$9.6 billion (i.e., = \$345 × 678,264 shares × 5 days × 6% × 5% × 2,734 ETFs). Similar calculations using VIS and VHT data, result in $\$ShadowTrading$ estimates of between \$360 million to \$1.1 billion, and \$800 million to \$2.5 billion, respectively.

The $\$ShadowTrading$ estimates using the three most frequently used ETFs in our treatment sample are closest to the $\$ShadowTrading$ estimates in Table 6 when winsorization is applied at the $5^{th}/95^{th}$ percentiles. Using this level of winsorization and taking the average across the three approaches to forming a control sample in Table 6, we estimate the dollar value of shadow trading to be approximately \$2.75

billion during the sample period or an average of $212 million per annum. This estimate should be regarded as a lower bound given the winsorization will tend to remove some of the shadow trading and we only examine shadow trading prior to M&As, thereby excluding shadow trading prior to other price-sensitive news announcements.

Whichever way we calculate them, our estimates of $\$ShadowTrading$ are economically meaningful and suggest that a significant amount of shadow trading occurs in ETFs.

< Figure 1 here >

In Figures 1 and 2, we break down $\$ShadowTrading$ estimated using winsorization at the $5^{th}/95^{th}$ percentiles by year and by industry, respectively. Similar to the findings reported in Section 4.3, we find that $\$ShadowTrading$ is relatively modest between 2009 and 2013 (i.e., averaging $150 million per year), that is during the period when ETFs were emerging as an investment vehicle. During the 2014-2020 period, as ETFs were used as a mainstream investment option, $\$ShadowTrading$ increases to an average of $360 million per year, peaking at approximately $500 million per year during 2015-2016. At the end of our sample period, $\$ShadowTrading$ reduces significantly, consistent with the declining proportion of shadow traders relative to significant increases in ETF volume and increases in regulatory attention towards shadow trading.

< Figure 2 here >

Figure 2 shows that the Health Care, Technology, and Industrial sectors have the largest $\$ShadowTrading$, consistent with the findings reported in Section 4.4. $\$ShadowTrading$ in both the Health Care and Technology industries exceeds $1 billion, accounting for more than 75% of the total $\$ShadowTrading$ during our sample period.

5. Falsification and robustness tests

We conduct several robustness tests. In our main analysis, we find strong evidence of shadow trading in same-industry ETFs likely to be used by insiders. Our first robustness test is a falsification test in which we re-define the treatment sample to include ETFs that are unlikely to be traded by insiders prior to M&As. The logic is that if in this sample we also observe abnormal trading prior to the M&A events, then our method is likely to capture a spurious result.

To undertake the falsification test, we apply the exact reverse filters that we used to create the sample of ETFs that are likely to be traded by insiders: (i) $Stock - ETF\ relatedness_i$ must be below the top quartile of the full sample of ETFs per deal; (ii) target firm market capitalization must be below the yearly median value; (iii) ETF market capitalization must be below the yearly median value; (iv) target firm announcement return must be below the yearly median value; and (v) M&A deal is rumored.

< Table 7 here >

Table 7 shows that ETFs that are not likely to be traded by insiders have *Abnormal volume* that is generally not statistically distinguishable from ETFs in the control sample. In the one case where the *Abnormal volume* is marginally significant at the 10% level, there is slightly less *Abnormal volume* in the falsification treatment sample than in the control sample (0.4925 < 0.50). These results from the falsification tests suggest that our main analysis is not capturing a spurious result.

We reach a similar conclusion using regressions reported in Table 8. The $Suspected_{i,x,t}$ coefficient estimate is statistically insignificant. This result contrasts with the regressions in our main analysis (Table 3) and supports the conclusion that insiders prefer to shadow trade using liquid ETFs that are closely related to large target firms subject to takeover bids.

< Table 8 here >

In our main tests, we apply several filters to construct the treatment sample of ETFs. As a robustness test, we re-define these filters and report our findings in Table 9. In Specification (i), (ii), and (iii), the target firm announcement return is below (rather than above) the median, positive only, and negative only, respectively. Across these specifications, we find that shadow trading occurs in 2-6% of ETFs in the treatment sample. However, only when the target firm announcement return is positive do we observe that *Abnormal volume* is significantly larger (at a 99% confidence level) in the treatment sample when compared to the control sample, consistent with insiders trading on positive news relating to the target firm (see $Suspected_{i,x,t}$ coefficient estimate = 0.0195 from the OLS regression test).

In Specification (iv) the target firm market capitalization is below (rather than above) the median. The percentile and OLS regression tests suggest reduced or insignificant levels of *Abnormal volume*, consistent with the target firm having an insignificant weighting of the same-industry ETF's total capitalization, and thus a negligible impact upon its price.

In Specification (v) and (vi), the ETF announcement return is positive only, and negative only, respectively. We find that when the ETF announcement return is positive (negative), shadow trading occurs in 3-5% (6-8%) of ETFs in the treatment sample. Overall, the results in Table 9 also justify the filters we used to create the treatment sample which are used to generate our main results. That is, shadow trading in

ETFs is more likely to occur in liquid ETFs which are closely related to large target firms which increase significantly in value following the acquisition bid.

< Table 9 here >

We also test the robustness of each filter (both individually and in groups) that is used to construct the treatment sample of ETFs. Table 10 reports the findings. In Specification (i) we remove the filter that the target firm announcement return is above the median. In Specification (ii) we remove the filter that the target firm market capitalization is above the median. In Specification (iii) we remove the filter that the ETF market capitalization is above the median. In Specification (iv) we remove the filter that the deal is rumored. In Specification (v) we choose the top-ten ETFs randomly (rather than by market capitalization). In Specification (vi) we choose the top-five (rather than the top-ten) ETFs by market capitalization. In Specification (vii) we remove all filters relating to the target firm (i.e., announcement return, market capitalization). In Specification (viii) we remove all ETF market capitalization filters. In Specification (ix) we remove all ETF and target firm filters (i.e., announcement return, market capitalization). In Specification (x) we require the 180-day rolling correlation between target firm and ETF returns to be above the median (rather than above the 75^{th} percentile). In Specification (xi) we remove the 180-day rolling correlation between target firm and ETF returns to be above the 75^{th} percentile filter. In Specification (xii) we require the 180-day rolling correlation between target firm and ETF returns to be above the 75^{th} percentile and remove all ETF and target firm filters.

Overall, our main results hold across all these robustness tests indicating that our main conclusions are not driven mechanically by any of the filters that are used to construct the treatment sample of ETFs.

< Table 10 here >

In our main tests, we calculate *Abnormal volume* during the [-5,-1] period prior to the M&A announcement date. In our next robustness test, we calculate *Abnormal volume* during the [-7,-1] and [-10,-1] periods prior to the M&A announcement date. Table 11 reports the results and shows that the abnormal trading that we detect in our main analysis is not overly sensitive to the choice of pre-event measurement window – evidence of shadow trading is present in all the windows that we examine.

< Table 11 here >

Finally, we also re-define our measurement of *ETF-stock relatedness* (i.e., the 180-day correlation between ETF and target firm returns) and reach similar conclusions to our main findings. In Table 12, we re-calculate *ETF-stock relatedness* using 30-day, 90-day, and 360-day periods, and using weekly returns during a 180-day period. In Table 13, we re-calculate 180-day correlations during the following periods prior to the M&A announcement date: [-181,-2], [-182,-3], [-185,-5], and [-190,-10].

< Table 12 here >

< Table 13 here >

6. Conclusion

This paper provides the first estimates of shadow trading in ETFs and sheds light on the characteristics of this form of insider trading. Using a bootstrap approach, we find robust evidence consistent with shadow trading in ETFs prior to M&A announcements. For ETFs likely to be traded by insiders, we observe abnormal levels of volume in 3-6% of ETFs on average prior to M&A announcements.

Through time, shadow trading has increased from 2009-2013 to 2014-2019 which corresponds with growing interest and liquidity in ETFs as they become a well-established investment vehicle. We find that shadow trading in ETFs amounts to at least $2.75 billion of trading over the last 13 years or $212 million per annum. Our evidence indicates that ETFs are not purely passive investment vehicles, but they also play a role in insider trading strategies.

We find that shadow trading in ETFs is more likely when insiders can strategically trade and hide their private information in liquid ETFs and when their private information is more valuable resulting in larger ETF trading profits. We find that shadow trading in ETFs prior to M&A announcements is most prevalent in the Health Care, Technology, and Industrial sectors, which is consistent with the higher levels of information asymmetry in these industries.

Our findings have policy implications. Through a better understanding of where and when insiders choose to trade, recognizing that can at times be in markets or instruments other than the underlying shares of a company, our results help guide surveillance efforts to reduce insider trading and improve the integrity of financial markets. If only the traditional, direct form of illegal insider trading is considered, then the total amount of insider trading may be underestimated as it fails to account for an economically meaningful amount of shadow trading. From a legal perspective, it is worth considering how adequately current insider trading legislation and case law are equipped to take enforcement actions against the large amounts of shadow trading documented in ETFs.

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Figure 1. Dollar value of shadow trading in ETFs through time

This figure plots yearly estimates of the dollar value of shadow trading in millions of dollars. The vertical axis plots $\$ShadowTrading$, which is the difference between the *Abnormal volume* in suspected same-industry ETFs (i.e., ETFs in the treatment sample) and *Abnormal volume* in a control sample of ETFs divided by 1,000 (as there are 1,000 observations in the control sample for each ETF-target firm-day in the treatment sample). The control sample is obtained from a Random-ETF/dates bootstrapped random distribution of 1,000 observations. We winsorize *Abnormal volume* at the ETF-day level at the $5^{th}/95^{th}$ percentiles. The sample period is January 1, 2009 to December 31, 2021 and we plot only the positive values.

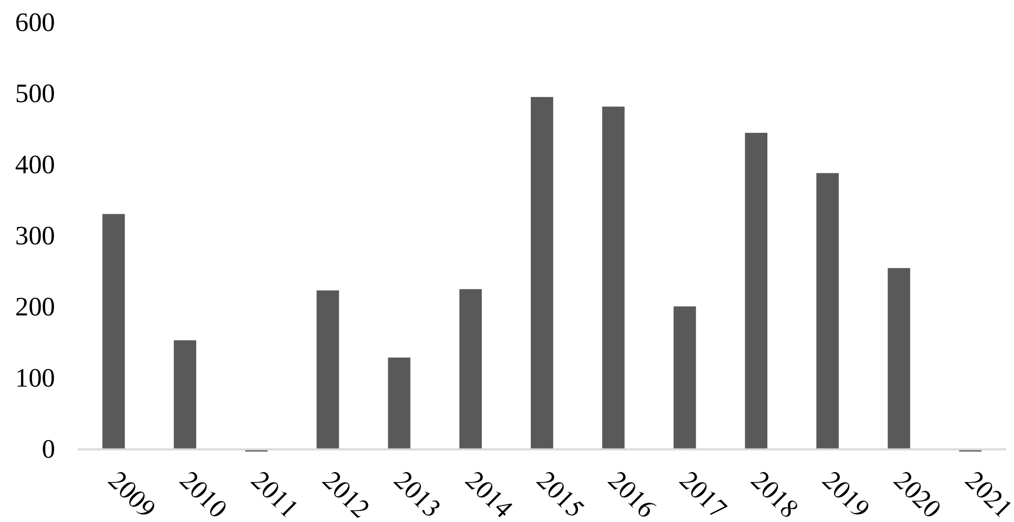

Figure 2. Dollar value of shadow trading in ETFs by industry

This figure plots estimates of the dollar value of shadow trading in ETFs in millions of dollars by industry. The vertical axis plots $\$ShadowTrading$, which is the difference between the *Abnormal volume* in suspected same-industry ETFs (i.e., ETFs in the treatment sample) and *Abnormal volume* in a control sample of ETFs divided by 1,000 (as there are 1,000 observations in the control sample for each ETF-target firm-day in the treatment sample). The control sample is obtained from a Random-ETF/dates bootstrapped random distribution of 1,000 observations. We winsorize *Abnormal volume* at the ETF-day level at the $5^{th}/95^{th}$ percentiles. The sample period is January 1, 2009 to December 31, 2021 and we plot only the positive values.

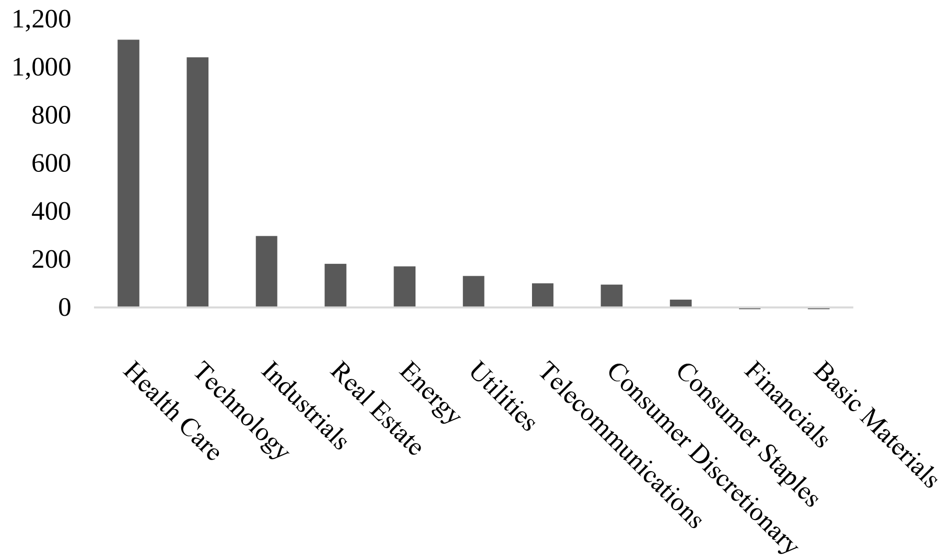

Table 1. M&A deal descriptive statistics

This table reports descriptive statistics for 2,734 M&A deals between January 1, 2009 and December 31, 2021. Panel A reports the characteristics of M&A deals. *Market capitalization* is the target firm market capitalization (expressed in millions), *TGTCAR* is the cumulative target firm abnormal return during the [-1,+1] period around the M&A announcement date, *Shares acquired* is the shares purchased by the acquiring firm in the M&A deal. Panel B reports the breakdown of M&A deals by *Deal form*, *Industry*, *Rumored deal*, and *Acquirer nation*.

Panel A: Deal characteristics					
	N	Mean	Std.Dev	Min	Max
Market capitalization	2,734	1,491.13	4,330.68	0.01	66,912.25
TGTCAR	2,734	0.20	0.37	-3.51	5.66
Shares acquired	2,734	97.49	8.86	50.00	100.00

Panel B: Breakdown of 2,734 M&A deals	
Deal form	
Merger	2,564/2,734 (94%)
Acquisition of majority interest	150/2,734 (5.5%)
Acquisition of assets	14/2,734 (0.5%)
Acquisition	4/2,734 (0.1%)
Acquisition of remaining interest	2/2,734 (<0.1%)
Industry	
Financials	695/2,734 (25%)
Health care	395/2,734 (14%)
Technology	387/2,734 (14%)
Consumer discretionary	345/2,734 (13%)
Industrials	278/2,734 (10%)
Energy	195/2,734 (7.1%)
Telecommunications	116/2,734 (4.2%)
Consumer Staples	98/2,734 (3.6%)
Basic Materials	87/2,734 (3.2%)
Real Estate	84/2,734 (3.1%)
Utilities	54/2,734 (2.0%)
Rumored deal	
Yes	303/2,734 (11%)
Acquirer nation	
United States	2,340/2,734 (86%)
Canada	97/2,734 (3.6%)
United Kingdom	54/2,734 (2.0%)
Japan	38/2,734 (1.4%)
France	27/2,734 (1.0%)
Germany	20/2,734 (0.7%)
China	17/2,734 (0.6%)
Switzerland	17/2,734 (0.6%)
Bermuda	13/2,734 (0.5%)
Netherlands	13/2,734 (0.5%)
Other	98/2,734 (3.6%)

Table 2. Percentile tests of shadow trading

This table compares the distribution of *Abnormal volume* in the treatment sample (ETFs most likely to have shadow trading) to three different bootstrapped random distributions of 1,000 observations (the control sample). The numbers in the table are the proportion of treatment deal-ETF pairs that have an Abnormal volume value that exceeds the 50th percentile of the control distribution, as well as the associated *p*-values (in parentheses) of whether that proportion is statistically different from the 50% that would be expected under the null hypothesis. The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). The sample comprises of 2,734 suspected deal-ETF pairs between January 1, 2009 and December 31, 2021. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively.

	Random-dates	Random-ETF	Random-ETF/dates
Abnormal volume	0.5388***	0.5563***	0.5618***
	(0.0000)	(0.0000)	(0.0000)

Table 3. Determinants of shadow trading using suspected ETFs

This table reports coefficient estimates from the following OLS regression using ETF-target firm-date observations (i, x, t):

$$ShadowTrading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$ShadowTrading_{i,x,t}$ is proxied using *Abnormal volume*, which is the abnormal ETF trading volume during the [-5,-1] period prior to the M&A announcement date. $Suspected_{i,x,t}$ is equal to one for suspected same-industry ETFs including the target firm (i.e., ETFs in the treatment sample) and zero for ETFs in the Random-ETF/dates control sample. $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample comprises of 2,734 suspected deal-ETF pairs between January 1, 2009 and December 31, 2021. Standard errors are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	$Abnormal\ volume_{i,x,t}$
$Intercept$	-0.0340
	(0.0480)
$Suspected_{i,x,t}$	0.0250***
	(0.0070)
$TGTMktCap_{i,x,t}$	0.0010
	(0.0010)
$TGTMB_{i,x,t}$	-0.0001
	(0.0001)
$TGTCAR_{i,x,t}$	-0.0070
	(0.0100)
$ETFMktCap_{i,x,t}$	-0.0030**
	(0.0020)
$ETFTurnover_{i,x,t}$	-0.0110***
	(0.0010)
N	56,236
Adj. R^2 (%)	5.70
ETF Fixed Effects	Yes
Month Fixed Effects	Yes

Table 4. Shadow trading in ETFs through time

This table examines shadow trading in ETFs through time using a percentile test and OLS regressions. In the percentile test, *Abnormal volume* is compared for suspected same-industry ETFs (the treatment sample) to the 50th percentiles of three different bootstrapped random distributions of 1,000 observations (the control sample). The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). This table also reports the $Suspected_{i,x,t}$ coefficient estimate from the following OLS regression using ETF-target firm-date observations (i, x, t):

$$Shadow\ trading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$Shadow\ trading_{i,x,t}$ is proxied using *Abnormal volume*. $Suspected_{i,x,t}$ is equal to one for treatment sample ETFs and zero for control sample ETFs using the Random-ETF/dates control sample. $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample comprises of 2,734 suspected deal-ETF pairs between January 1, 2009 and December 31, 2021. p-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	N		Percentile test			Regression
Year(s)	ETFs	Deals	Random-dates	Random-ETF	Random-ETF/dates	$Suspected_{i,x,t}$
2009-2011	924	109	0.5032	0.5595***	0.5281*	0.0042
			(0.8436)	(0.0003)	(0.0871)	(0.7011)
2012-2013	392	50	0.5230	0.5209	0.5383	0.0040
			(0.3639)	(0.5641)	(0.1299)	(0.8091)
2014- 2015	191	26	0.6597***	0.5707*	0.6911***	0.0647**
			(0.0000)	(0.0505)	(0.0000)	(0.0113)
2016-2017	380	52	0.5895***	0.5816***	0.6105***	0.0527***
			(0.0004)	(0.0014)	(0.0000)	(0.0058)
2018-2019	315	38	0.6127***	0.5683**	0.6444***	0.0349**
			(0.0001)	(0.0152)	(0.0000)	(0.0474)
2020-2021	351	42	0.4644	0.5043	0.4872	-0.0065
			(0.1825)	(0.8730)	(0.6316)	(0.6962)

Table 5. Shadow trading using suspected ETFs by industry

This table examines shadow trading in ETFs by industry using a percentile test and OLS regressions. In the percentile test, *Abnormal volume* is compared for suspected same-industry ETFs (the treatment sample) to the 50th percentiles of three different bootstrapped random distributions of 1,000 observations (the control sample). The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). This table also reports the $Suspected_{i,x,t}$ coefficient estimate from the following OLS regression using ETF-target firm-date observations (i, x, t):

$$Shadow\ trading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$Shadow\ trading_{i,x,t}$ is proxied using *Abnormal volume*. $Suspected_{i,x,t}$ is equal to one for treatment sample ETFs and zero for control sample ETFs using the Random-ETF/dates control sample. $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample comprises of 2,734 suspected deal-ETF pairs between January 1, 2009 and December 31, 2021. p-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	N		Percentile test			Regression
Industry	ETFs	Deals	Random-dates	Random-ETF	Random-ETF/dates	$Suspected_{i,x,t}$
Health care	541	73	0.5287	0.5490**	0.5582***	0.0439***
			(0.1828)	(0.0225)	(0.0066)	(0.0022)
Real estate	69	9	0.5797	0.6087*	0.6232**	0.0825
			(0.1874)	(0.0706)	(0.0398)	(0.1024)
Consumer discretionary	234	35	0.5598*	0.5214	0.5556*	0.0089
			(0.0671)	(0.5145)	(0.0892)	(0.6427)
Industrials	475	53	0.5221	0.5411*	0.5411*	0.0204
			(0.3358)	(0.0735)	(0.0735)	(0.1760)
Technology	548	63	0.5584***	0.6223***	0.5876***	0.0586***
			(0.0062)	(0.0000)	(0.0000)	(0.0000)
Telecommunications	44	13	0.5227	0.5455	0.5000	0.0263
			(0.7669)	(0.5526)	(1.0000)	(0.6055)
Financials	345	37	0.4754	0.4870	0.4957	-0.0220
			(0.3608)	(0.6287)	(0.8720)	(0.1592)
Energy	242	26	0.5785**	0.5207	0.6157***	0.0362*
			(0.0143)	(0.5215)	(0.0003)	(0.0688)
Basic materials	152	18	0.5592	0.5526	0.5724*	-0.0396
			(0.1449)	(0.1953)	(0.0743)	(0.1988)
Utilities	45	6	0.6889***	0.6444*	0.7111***	0.0821
			(0.0096)	(0.0515)	(0.0035)	(0.3505)
Consumer staples	39	8	0.5385	0.4615	0.4872	-0.1273
			(0.6371)	(0.6371)	(0.8752)	(0.1703)

Table 6. Dollar value of shadow trading in ETFs

This table reports estimates of the dollar value of shadow trading in millions of dollars. $\$ShadowTrading$ is the difference between the *Abnormal volume* in suspected same-industry ETFs (i.e., ETFs in the treatment sample) and *Abnormal volume* in the control sample of ETFs, divided by 1,000 (as there are 1,000 observations in the control sample for each ETF-target firm-day in the treatment sample). The three control samples are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. We report $\$ShadowTrading$ with no winsorization of *Abnormal volume*, and winsorization at the $1^{st}/99^{th}$ and $5^{th}/95^{th}$ percentiles. The sample period is January 1, 2009 to December 31, 2021.

		$\$ShadowTrading$	
Winsorization	Random-dates	Random-ETF	Random-ETF/dates
None	6,112	48,588	68,137
$1^{st}/99^{th}$	8,808	13,712	15,337
$5^{th}/95^{th}$	2,954	2,410	2,890

Table 7. Falsification test using ETFs that are unlikely to be used for shadow trading

This table compares the distribution of *Abnormal volume* in a false treatment sample (same-industry ETFs that are unlikely to have shadow trading) to three different bootstrapped random distributions of 1,000 observations (the control sample). The numbers in the table are the proportion of treatment deal-ETF pairs that have an Abnormal volume value that exceeds the 50^{th} percentile of the control distribution, as well as the associated *p*-values (in parentheses) of whether that proportion is statistically different from the 50% that would be expected under the null hypothesis. The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). The sample comprises of 13,806 unsuspected deal-ETF pairs between January 1, 2009 and December 31, 2021. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively.

	Random-dates	Random-ETF	Random-ETF/dates
Abnormal volume	0.5064	0.4925*	0.4970
	(0.1298)	(0.0796)	(0.4853)

Table 8. Falsification tests using regressions

This table reports coefficient estimates from the following OLS regression using ETF-target firm-date observations (i, x, t):

$$ShadowTrading_{i,x,t} = \mu_i + \mu_m + \beta_1 Unsuspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$ShadowTrading_{i,x,t}$ is proxied using *Abnormal volume*, which is the abnormal ETF trading volume during the [-5,-1] period prior to the M&A announcement date. $Unsuspected_{i,x,t}$ is equal to one for same-industry ETFs that are unlikely to be used for shadow trading and zero for other ETFs (i.e., ETFs in the Random-ETF/dates control sample). $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample comprises 13,806 unsuspected deal-ETF pairs between January 1, 2009 and December 31, 2021. Standard errors are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	$Abnormal\ volume_{i,x,t}$
$Intercept$	-0.0150
	(0.0210)
$Unsuspected_{i,x,t}$	0.0010
	(0.0030)
$TGTMktCap_{i,x,t}$	0.0002
	(0.0002)
$TGTMB_{i,x,t}$	-0.0000
	(0.0000)
$TGTCAR_{i,x,t}$	0.0003
	(0.0020)
$ETFMktCap_{i,x,t}$	-0.0060***
	(0.0010)
$ETFTurnover_{i,x,t}$	-0.0080***
	(0.0004)
N	268,385
Adj. R^2 (%)	6.40
ETF Fixed Effects	Yes
Month Fixed Effects	Yes

Table 9. Alternative specifications to construct treatment sample of ETFs

This table examines the robustness of the percentile test and OLS regressions, using different specifications to identify suspected same-industry ETFs that include the target firms (treatment sample). In Specification (i), (ii), and (iii), the target firm announcement return is below (rather than above) the median, positive only, and negative only, respectively. In Specification (iv) the target firm market capitalization is below (rather than above) the median. In Specification (v) and (vi), the ETF announcement return is positive only, and negative only, respectively. In the percentile test, *Abnormal volume* is compared for suspected same-industry ETFs (the treatment sample) to the 50th percentiles of three different bootstrapped random distributions of 1,000 observations (the control sample). The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). This table also reports the $Suspected_{i,x,t}$ coefficient estimate from the following OLS regression using ETF-target firm-date observations (i, x, t):

$$Shadow\ trading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$Shadow\ trading_{i,x,t}$ is proxied using *Abnormal volume*. $Suspected_{i,x,t}$ is equal to one for treatment sample ETFs and zero for control sample ETFs using the Random-ETF/dates control sample. $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample period is between January 1, 2009 and December 31, 2021. p-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	N		Percentile test			Regression
Specification	ETFs	Deals	Random-dates	Random-ETF	Random-ETF/dates	$Suspected_{i,x,t}$
(i)	2,816	351	0.5075	0.5458***	0.5408***	0.0090
			(0.4288)	(0.0000)	(0.0000)	(0.1651)
(ii)	5,141	645	0.5246***	0.5553***	0.5516***	0.0195***
			(0.0004)	(0.0000)	(0.0000)	(0.0000)
(iii)	432	50	0.5301	0.5556**	0.5440*	0.0053
			(0.2113)	(0.0207)	(0.0675)	(0.7706)
(iv)	612	90	0.4542**	0.5065	0.4641*	0.0058
			(0.0235)	(0.7467)	(0.0753)	(0.6928)
(v)	1,633	306	0.5279**	0.5395***	0.5456***	0.0315***
			(0.0243)	(0.0014)	(0.0002)	(0.0002)
(vi)	1,101	244	0.5631***	0.5731***	0.5767***	0.0204**
			(0.0000)	(0.0000)	(0.0000)	(0.0423)

Table 10. Robustness of specifications to construct treatment sample of ETFs

This table examines the robustness of the percentile test and OLS regressions, using different specifications to identify suspected same-industry ETFs that include the target firms (treatment sample). In Specification (i) we remove the filter that the target firm announcement return is above the median. In Specification (ii) we remove the filter that the target firm market capitalization is above the median. In Specification (iii) we remove the filter that the ETF market capitalization is above the median. In Specification (iv) we remove the filter that the deal is rumored. In Specification (v) we choose the top-ten ETFs randomly (rather than by market capitalization). In Specification (vi) we choose the top-five (rather than the top-ten) ETFs by market capitalization. In Specification (vii) we remove all filters relating to the target firm (i.e., announcement return, market capitalization). In Specification (viii) we remove all ETF market capitalization filters. In Specification (ix) we remove all ETF and target firm filters (i.e., announcement return, market capitalization). In Specification (x) we require the 180-day rolling correlation between target firm and ETF returns to be above the median (rather than above the 75^{th} percentile). In Specification (xi) we remove the 180-day rolling correlation between target firm and ETF returns to be above the 75^{th} percentile filter. In Specification (xii) we require the 180-day rolling correlation between target firm and ETF returns to be above the 75^{th} percentile and remove all ETF and target firm filters. In the percentile test, *Abnormal volume* is compared for suspected same-industry ETFs (the treatment sample) to the 50^{th} percentiles of three different bootstrapped random distributions of 1,000 observations (the control sample). The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). This table also reports the $Suspected_{i,x,t}$ coefficient estimate from the following OLS regression using ETF-target firm-date observations (i,x,t):

$$Shadow\ trading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$Shadow\ trading_{i,x,t}$ is proxied using *Abnormal volume*. $Suspected_{i,x,t}$ is equal to one for treatment sample ETFs and zero for control sample ETFs using the Random-ETF/dates control sample. $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample period is between January 1, 2009 and December 31, 2021. p-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 10. Robustness of specifications to construct treatment sample of ETFs (continued)

Specification	N		Percentile test			Regression
	ETFs	Deals	Random-dates	Random-ETF	Random-ETF/dates	$Suspected_{i,x,t}$
(i)	5,573	695	0.5234***	0.5528***	0.5510***	0.0166***
			(0.0005)	(0.0000)	(0.0000)	(0.0003)
(ii)	3,356	432	0.5256***	0.5471***	0.5423***	0.0221***
			(0.0030)	(0.0000)	(0.0000)	(0.0005)
(iii)	2,889	346	0.5333***	0.5427***	0.5510***	0.0181***
			(0.0003)	(0.0000)	(0.0000)	(0.0056)
(iv)	3,110	386	0.5248***	0.5437***	0.5508***	0.0233***
			(0.0057)	(0.0000)	(0.0000)	(0.0001)
(v)	2,734	341	0.5331***	0.5382***	0.5437***	0.0235***
			(0.0005)	(0.0001)	(0.0000)	(0.0002)
(vi)	1,531	341	0.5291**	0.5643***	0.5643***	0.0220***
			(0.0229)	(0.0000)	(0.0000)	(0.0056)
(vii)	6,755	856	0.5192***	0.5491***	0.5476***	0.0196***
			(0.0016)	(0.0000)	(0.0000)	(0.0000)
(viii)	2,889	346	0.5276***	0.5203**	0.5262***	0.0166***
			(0.0031)	(0.0301)	(0.0050)	(0.0072)
(ix)	3,557	441	0.5188**	0.5145*	0.5213**	0.0103*
			(0.0261)	(0.0856)	(0.0114)	(0.0848)
(x)	4,006	447	0.5225***	0.5574***	0.5532***	0.0191***
			(0.0044)	(0.0000)	(0.0000)	(0.0000)
(xi)	5,041	536	0.5240***	0.5532***	0.5542***	0.0124***
			(0.0006)	(0.0000)	(0.0000)	(0.0075)
(xii)	8,640	1,066	0.5098*	0.5172***	0.5148***	0.0108***
			(0.0685)	(0.0014)	(0.0060)	(0.0034)

Table 11. Alternative definitions of pre-event windows

This table examines the robustness of the percentile test and OLS regressions to using different pre-event windows: seven and ten-days (rather than five-days) prior to the M&A announcement date. In the percentile test, *Abnormal volume* is compared for suspected same-industry ETFs (the treatment sample) to the 50^{th} percentiles of three different bootstrapped random distributions of 1,000 observations (the control sample). The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). This table also reports the $Suspected_{i,x,t}$ coefficient estimate from the following OLS regression using ETF-target firm-date observations (i, x, t):

$$Shadow\ trading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$Shadow\ trading_{i,x,t}$ is proxied using *Abnormal volume*. $Suspected_{i,x,t}$ is equal to one for treatment sample ETFs and zero for control sample ETFs using the Random-ETF/dates control sample. $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample period is between January 1, 2009 and December 31, 2021. p-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	N		Percentile test			Regression
Specification	ETFs	Deals	Random-dates	Random-ETF	Random-ETF/dates	$Suspected_{i,x,t}$
[-7,-1]	2,734	341	0.5368***	0.5458***	0.5439***	0.0232***
			(0.0001)	(0.0000)	(0.0000)	(0.0001)
[-10,-1]	2,734	341	0.5248**	0.5316***	0.5282***	0.0150***
			(0.0105)	(0.0011)	(0.0036)	(0.0037)

Table 12. Alternative ETF-stock relatedness windows

This table examines the robustness of the percentile test and OLS regressions to alternative definitions of *ETF-stock relatedness* using the 30-day, 90-day, 360-day (rather than the 180-day) correlation between ETF and target firm returns. In the percentile test, *Abnormal volume* is compared for suspected same-industry ETFs (the treatment sample) to the 50th percentiles of three different bootstrapped random distributions of 1,000 observations (the control sample). The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). This table also reports the $Suspected_{i,x,t}$ coefficient estimate from the following OLS regression using ETF-target firm-date observations (i, x, t):

$$Shadow\ trading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$Shadow\ trading_{i,x,t}$ is proxied using *Abnormal volume*. $Suspected_{i,x,t}$ is equal to one for treatment sample ETFs and zero for control sample ETFs using the Random-ETF/dates control sample. $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample period is between January 1, 2009 and December 31, 2021. p-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	N		Percentile test			Regression
Specification	ETFs	Deals	Random-dates	Random-ETF	Random-ETF/dates	$Suspected_{i,x,t}$
30-day	3,022	379	0.5282***	0.5387***	0.5465***	0.0174***
			(0.0022)	(0.0000)	(0.0000)	(0.0044)
90-day	2,944	347	0.5276***	0.5398***	0.5456***	0.0130**
			(0.0035)	(0.0000)	(0.0000)	(0.0256)
360-day	2,517	315	0.5149	0.5324***	0.5284***	0.0152**
			(0.1350)	(0.0011)	(0.0043)	(0.0430)
180-day weekly	2,289	254	0.5256**	0.5282***	0.5400***	0.0142**
			(0.0144)	(0.0070)	(0.0001)	(0.0300)

Table 13. Alternative ETF-stock relatedness periods

This table examines the robustness of the percentile test and OLS regressions to alternative definitions of *ETF-stock relatedness* during the 180-day period ending two, three, five, and ten days (rather than one day) prior to the M&A announcement. In the percentile test, *Abnormal volume* is compared for suspected same-industry ETFs (the treatment sample) to the 50^{th} percentiles of three different bootstrapped random distributions of 1,000 observations (the control sample). The random distributions are: (i) Random-dates, comparing suspected same-industry ETFs that include the target firm to the same ETF on random dates, (ii) Random-ETF, comparing suspected same-industry ETFs that include the target firm to random ETFs on the same date, and (iii) Random-ETF/dates, comparing suspected same-industry ETFs that include the target firm to random ETFs on random dates. Abnormal ETF trading volume is measured during the [-5,-1] period prior to the M&A announcement date (*Abnormal volume*). This table also reports the $Suspected_{i,x,t}$ coefficient estimate from the following OLS regression using ETF-target firm-date observations (i, x, t):

$$Shadow\ trading_{i,x,t} = \mu_i + \mu_m + \beta_1 Suspected_{i,x,t} + \sum_j \gamma_j\, TGTControls_{j,x,t} + \sum_k \gamma_k\, ETFControls_{k,i,,t} + \varepsilon_{i,x,t},$$

$Shadow\ trading_{i,x,t}$ is proxied using *Abnormal volume*. $Suspected_{i,x,t}$ is equal to one for treatment sample ETFs and zero for control sample ETFs using the Random-ETF/dates control sample. $TGTMktCap_{x,t}$ is the market capitalization of the target firm expressed in log form, $TGTMB_{x,t}$ is the market-to-book value of the target firm's assets, $TGTCAR_{x,t}$ is the cumulative target firm abnormal return during the period [-1,+1] around the M&A announcement date, $ETFMktCap_{i,x,t}$ is the market capitalization of the ETF expressed in log form, $ETFTurnover_{i,x,t}$ is the average traded volume by the average number of shares of the ETF. The sample period is between January 1, 2009 and December 31, 2021. p-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	N		Percentile test			Regression
Specification	ETFs	Deals	Random-dates	Random-ETF	Random-ETF/dates	$Suspected_{i,x,t}$
[-181,-2]	2,740	343	0.5374***	0.5501***	0.5550***	0.0247***
			(0.0001)	(0.0000)	(0.0000)	(0.0001)
[-182.-3]	2,733	340	0.5423***	0.5558***	0.5620***	0.0268***
			(0.0000)	(0.0000)	(0.0000)	(0.0000)
[-185,-5]	2,723	342	0.5400***	0.5582***	0.5615***	0.0246***
			(0.0000)	(0.0000)	(0.0000)	(0.0001)
[-190,-10]	2,693	336	0.5377***	0.5514***	0.5581***	0.0219***
			(0.0001)	(0.0000)	(0.0000)	(0.0005)