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Innovation and Informed Trading: Evidence from Industry ETFs

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We empirically examine the impact of industry exchange-traded funds (IETFs) on informed trading and market efficiency. We find that IETF short interest spikes simultaneously with hedge fund holdings on the member stock before positive earnings surprises, reflecting *long-the-stock/short-the-ETF* activity. This pattern is stronger among stocks with high industry risk exposure. A difference-in-difference analysis on the ETF inception event shows that IETFs reduce post-earnings-announcement drift more among stocks with high industry risk exposure, suggesting that IETFs improve market efficiency. We also find that the short interest ratio of IETFs positively predicts IETF returns, consistent with the hedging role of IETFs. (*JEL* G12, G14)

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Few financial innovations in recent times have had the impact of exchange-traded funds (ETFs). Given that there are now approximately 5,000 ETFs with

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assets exceeding \$4.0 trillion, there is little disagreement that passive investing via ETFs poses a "disruptive innovation" for the entire asset management industry.[1] For many investors, the main benefit of ETFs is providing a more liquid, lower-cost alternative to mutual funds. For others, the benefit is access to previously unavailable asset classes. In this paper, we argue that another, perhaps underappreciated, benefit is an expanded ability to hedge. We demonstrate that this aspect of ETFs directly affects the nature of informed trading and the efficiency of the market.

The hypothesis that ETFs can facilitate hedging for informed investors is suggested by the theory of financial innovation. In an early important paper, Dow (1998) argues that introducing a new security can help informed investors hedge risk and thus encourage more informed trading. Viewed from this perspective, the effect of financial innovation is akin to the effect of reducing arbitrage constraints. The idea of using ETFs to hedge is also widely discussed in practice. For example, *Bloomberg* reported that "hedge funds mainly use ETFs to take short positions. …As a group, hedge funds have \$105 billion in short ETF positions—-more than double their \$43 billion in long positions. …The funds' shorts don't necessarily indicate bearish sentiment, but rather are used to hedge out part of the market in order to isolate a long position" (Balchunas 2017).

We investigate this hedging role of ETFs by focusing on industry ETFs. The risk of a stock includes market, industry, and firm-specific risk. An informed trader hoping to profit from firm-specific information will want to hedge market and industry risk. While index futures or index ETFs are used to hedge market risk, industry ETFs provide a low-cost vehicle to hedge industry risk. When informed investors use industry ETFs to hedge industry risk and exploit positive firm-specific information, the short sale of the industry ETF belongs to the short leg of a *long-the-stock/short-the-ETF* strategy (termed long-short activity for brevity). Since hedge funds are likely candidates for adopting such a strategy, hedge fund trading on a stock largely captures the long leg of the long-short activity. By combining information on hedge fund trading in a stock and short interest on the industry ETF, we are able to show how the industry ETF affects both informed trading and market efficiency.

Specifically, we identify an ETF as an industry ETF if more than 30% of its portfolio holdings are in one of the Fama-French 12 industries; then, we take two steps to measure long-short activity. First, for each stock in each quarter, we follow Chen, Da, and Huang (2019) and measure hedge fund trading by abnormal hedge fund holdings, defined as the number of shares of a stock held by hedge funds at the quarter end minus the average number of shares held by hedge funds in the past four quarters, divided by the number of shares outstanding at the quarter end. Similarly, for each ETF in each quarter, we

[1] Ananth Madhavan (2016) makes the case for such disruptive innovation in his book.

consider abnormal short interest, which is the short interest ratio (*SIR*) of the ETF at the quarter end minus the average *SIR* of the ETF in the past four quarters. Second, we construct a dummy variable to capture long-short activity. That is, we consider an industry ETF and one of its constituent stock as a pair, and for each ETF-stock pair in a given quarter, we define a dummy variable to equal one if both abnormal hedge fund holdings of this stock and abnormal *SIR* of this ETF are above their 80th percentiles in the sample.[2] Intuitively, this dummy variable captures the simultaneous spikes in abnormal hedge fund holdings on a stock and abnormal short interest in the stock's parent industry ETF.

Based on this measure of long-short activity, we investigate our hypotheses that (1) investors use a *long-the-stock/short-the-ETF* strategy with the industry ETF to exploit firm-specific information and (2) the industry ETF improves market efficiency. We provide a variety of tests, with our main focus on long-short activity prior to earnings announcements and post-earnings-announcement drift (PEAD). Specifically, using earnings surprises (defined as the standardized unexpected earnings following Livnat and Mendenhall 2006) to measure firm-specific information, we find that long-short activity surges before a positive earnings surprise announcement, suggesting that investors use the *long-the-stock/short-the-ETF* strategy to exploit their information about firm earnings. Moreover, we find long-short activity prior to positive earnings surprises is stronger among stocks with high industry risk exposure, consistent with better hedging of industry risk using industry ETFs for such stocks.

Motived by strong evidence of long-short activity among member stocks of industry ETFs, we expect that market efficiency to be improved among member stocks. Examining the market efficiency implication of industry ETFs in the context of PEAD, we find that being a member of an industry ETF reduces PEAD. To alleviate concerns that this result can be driven by the differences in information environments between member stocks of the industry ETF and nonmember stocks, we use a propensity score matching (PSM) approach to control for firm characteristics related to market efficiency (e.g., firm size, institutional ownership, and analyst coverage). We find strong evidence that the PEAD-reducing effect with industry ETF membership still holds. We are aware that even for nonmember stocks, investors could also use industry ETFs to hedge industry risk. That said, we find that stocks belonging to industry ETFs have higher industry risk exposure than nonmember stocks. This finding suggests that the PEAD-reducing effect with industry ETF membership is at least partially reflecting the improvement on industry risk hedging with industry ETFs for stocks with high industry risk exposure.

To address the concern that the PSM approach may not perfectly control for potential omitted variables that determine not only inclusion in the ETF but also market efficiency, we focus on member stocks of the industry ETF and conduct

[2] When a stock belongs to multiple industry ETFs, it is paired with each ETF. For each ETF-stock pair, we refer to the ETF as the parent ETF of the paired stock.

a difference-in-difference (*diff-in-diff*) analysis.[3] Motived by the finding that long-short activity is more pronounced among stocks with high industry risk exposure, in this *diff-in-diff* analysis we compare PEAD for member stocks with high and low industry risk exposure, within 2 years before and after the inception of the industry ETF. We first demonstrate that member stocks with high and low industry risk exposure are not significantly different with respect to firm characteristics related to market efficiency. Second, in the *diff-in-diff* analysis, we find that after ETF inception, the member stocks with the strongest reduction in PEAD are those with the highest industry risk exposure. We also examine the "parallel trend" assumption in the *diff-in-diff* analysis and confirm that PEAD is not significantly different between member stocks with high and low industry risk exposure in each year before the inception of the industry ETF. This finding suggests that the PEAD-reducing effect in the *diff-in-diff* analysis comes from the inception of the industry ETF rather than the time trend.

Finally, we examine how industry ETFs affect market efficiency in the context of arbitrage risk on stocks. If industry ETFs facilitate informed investors' arbitrage activity among their member stocks, then member stocks should experience decreases in arbitrage risk. To test this argument, we follow Wurgler and Zhuravskaya (2002) to calculate arbitrage risk, which measures the extent to which stocks' return variation can be hedged by their substitute stocks. We find that the inception of the industry ETF reduces the arbitrage risk of member stocks.[4]

We conduct a variety of tests to corroborate our evidence. First, we show that our results are robust to alternative cutoffs for the weights to define an industry ETF, the abnormal hedge fund holdings of the stock, and the abnormal *SIR* of the stock's parent ETF. Second, we show that our results hold when using an alternative measure of earnings surprises based on analyst forecasts. Third, we use nonindustry ETFs as a placebo test and find that nonindustry ETF membership is not associated with a PEAD-reducing effect, highlighting the uniqueness of the industry ETF in improving market efficiency. Fourth, we conduct an additional cross-sectional study and show that stocks whose pair stocks have high shorting costs have stronger long-short activity and experience a greater PEAD reduction effect. Last, we confirm that short interest in industry ETFs is unlikely to be driven by trading from retail investors.

Overall, our results show important, and pervasive, effects of industry ETFs on informed trading and market efficiency. Our results also have intriguing asset pricing implications for the return predictability of industry ETFs. If informed investors short industry ETFs to hedge industry risk and exploit positive information of the member stock, then short sales of industry ETFs contain positive information on the member stock. To the extent that the

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3 We thank the anonymous referee for suggesting this *diff-in-diff* analysis.

4 We thank the anonymous referee for suggesting the test on arbitrage risk.

market underreacts to this information, short interest in the industry ETF should positively predict the future return on the ETF since the positive information on the member stock will eventually be incorporated into the ETF. We confirm this prediction by showing that the changes in *SIR* positively predict the future ETF return as well as the percentage change in the net asset value of the industry ETF. Given the large amount of evidence showing that *SIR* negatively predicts stock returns (e.g., Diether, Lee, and Werner 2009), our finding is surprising, but it is consistent with the hedging-motivated short sale on industry ETFs.

Our paper contributes to the literature along several aspects. Our study is motivated by the theoretical literature on financial innovation which shows that a new security can complete the financial market (Duffie and Rahi 1995), leading to more risk sharing (Simsek 2013a, 2013b), more optimal portfolios (Chen 1995), and more informed trading (Dow 1998). A growing body of literature studies the ETF as a specific financial innovation. Cong and Xu (2016) show that introducing composite securities facilitates informative trading on common risk factors. Bhattacharya and O'Hara (2018) show that the intermarket information linkages in ETFs may exacerbate market instability. Our research provides direct evidence showing that the industry ETF as a financial innovation facilitates informed trading and improves market efficiency.

Our paper is closely related to empirical studies on ETFs. One strand of these studies shows that ETFs increase volatility/comovement and harm liquidity. Ben-David, Franzoni, and Moussawi (2018) find that ETF arbitrage activity increases nonfundamental volatility on underlying stocks. Da and Shive (2018) show that ETF arbitrage contributes to return comovement. Pan and Zeng (2019) show that the intermarket liquidity mismatch in ETFs generates market instability. Israeli, Lee, and Sridharan (2017) find that ETF ownership increases the bid-ask spread on stocks. Other studies attempt to understand how ETFs affect market efficiency (see Madhavan and Sobczyk 2016; Easley et al. 2020; Glosten, Nallareddy, and Zou 2020). By focusing on how industry ETFs facilitate hedging, our study not only improves the understanding of how ETFs affect financial markets but also helps by suggesting the optimal design of the ETF product.

Our results also add to the literature on short selling. A large amount of evidence shows that short interest negatively predicts stock returns, and the literature generally agrees that short sellers speculate on negative information (see Asquith, Pathak, and Ritter 2005; and Diether, Lee, and Werner 2009). However, short selling can also be motivated by hedging. Utilizing institutional features of the Hong Kong stock market, Hwang, Liu, and Xu (2019) provide evidence on hedging-motivated short selling. They find that the emergence of shortable stocks causes hedgers to buy seemingly underpriced stocks more aggressively, essentially using paired stocks to hedge industry risk. In contrast to Hwang, Liu, and Xu (2019), we focus on industry ETFs as hedging vehicles and show that industry ETFs improve market efficiency. Furthermore, we present novel asset pricing implications that are not investigated by Hwang, Liu, and Xu (2019).

1. Hypotheses Development

In this section, we develop hypotheses to guide our empirical analysis of the effects of industry ETFs on informed trading and market efficiency. When informed investors use the *long-the-stock/short-the-ETF* strategy with industry ETFs to exploit positive firm-specific information, it is natural to expect simultaneous spikes in trading from hedge funds as informed investors on a stock and short interest in the stock's parent industry ETF prior to the announcement of positive firm-specific news. Using the earnings surprise (*SUE*) to measure firm-specific news of a stock, we formalize our first hypothesis as follows:

Hypothesis 1 (*long-the-stock/short-the-ETF* prior to positive earnings surprises).
If short interest in the industry ETF belongs to the short leg of the long-the-stock/short-the-ETF strategy, *then there are simultaneous spikes in hedge funds' long positions on the stock and short interest in the stock's parent ETF before the stock announces a positive* SUE.

Since investors use the *long-the-stock/short-the-ETF* strategy to immunize portfolios against industry risk, long-short activity varies across stocks due to different hedging needs of industry risk. Intuitively, when a stock has high industry risk exposure, investors must hedge more industry risk. Therefore, we expect this long-short activity to be more pronounced among stocks with high industry risk exposure. Based on this cross-sectional feature, we have the following subhypothesis:

Hypothesis 1.a (*long-the-stock/short-the-ETF* and industry risk exposure).
The relation between long-short activity and positive SUE *is more pronounced among stocks with high industry risk exposure.*

Long-short activity with industry ETFs has important implications for market efficiency. If industry ETFs help informed investors hedge industry risk, then informed investors can better trade on firm-specific information. Consequently, the market incorporates more information and market efficiency improves. We use PEAD to test the market efficiency implication. If long-short activity facilitates investors' trading on firm-specific information, we should see smaller PEAD, indicating a more efficient market. We formalize our second hypothesis as follows:

Hypothesis 2 (The industry ETF and market efficiency).
If the industry ETF helps investors immunize industry risk and thus better trade on firm-specific information, then we expect the industry ETF to reduce PEAD for its constituent stocks.

To better illustrate the economic intuitions for these hypotheses, we provide a suggestive model in Internet Appendix B.

2. Data Description and Sample Statistics

Our study mainly uses two data sets. The first data set contains information on U.S. industry ETFs, including short interest and holdings. The second data set contains earnings announcements of all publicly listed firms. We complement these two data sets with a variety of related data, such as hedge (non-hedge) fund holdings. Our sample period is from January 1999 to December 2017.

2.1 ETF-level data

2.1.1 The equity ETF. We first obtain a list of U.S. equity ETFs from the CRSP Survivor-Biased-Free Mutual Fund database. We identify a fund as an ETF if the "et_flag" of the fund is "F." Additionally, we require these funds to have a CRSP share code of either "44" or "73." To focus on nonsynthetic U.S. equity ETFs, we drop funds whose names contain "bond," "bear," or "hedged." Then we merge our list with a snapshot of all U.S. equity ETFs from ETFDB in June 2018.[5] For each ETF, we track its holdings from the inception date to December 2017 based on 13F data from Thomson Reuters. We require our sample ETFs to have at least 80% investment in U.S. common stocks. Our final sample consists of 508 U.S. equity ETFs, which is close to the sample size used in prior studies.[6]

2.1.2 Industry ETFs. We identify industry ETFs based on holdings. We match an ETF's holdings with the Fama-French 12 industry classification and then identify the industry in which the ETF has the most investment. To identify an industry ETF, we require that the dominant industry constitutes at least 30% of the ETF's portfolio holdings. This requirement gives us 244 industry ETFs. We filter out ETFs whose names contain "value," "growth," "Russell," "dividend," "momentum," or "dynamic" to ensure that the ETF primarily aims for a specific industry coverage. After filtering, we are left with 144 ETFs. We further require that the ETFs consist of at least 30 stocks.[7] Finally, we obtain 121 industry ETFs covering 10 of 12 Fama-French industries. Figure 1 shows the total net asset value and the number of industry ETFs in our sample.

2.1.3 The price, volume, and short interest data for equity ETFs. We obtain monthly price and volume data for our ETF sample from CRSP. The monthly short interest for industry ETFs is obtained from COMPUSTAT.[8] For

[5] ETFDB is a website providing detail information on ETF; see www.etfdb.com for details.

[6] Glosten, Nallareddy, and Zou (2020) identify 447 ETFs between 2004 and 2013; Da and Shive (2018) identify 549 ETFs between 2006 and 2013.

[7] As implied by the Law of Large Numbers, firm-specific risk is largely diversified in industry ETFs with more than 30 stocks. This type of industry ETF can better hedge industry risk (results are robust to the removal of this requirement).

[8] The COMPUSTAT short interest file only started covering NASDAQ stocks from 2003. Since the 11 industry ETFs in our sample that are traded on NASDAQ were introduced in 2011, our data on industry ETF short interest are also obtained from COMPUSTAT.

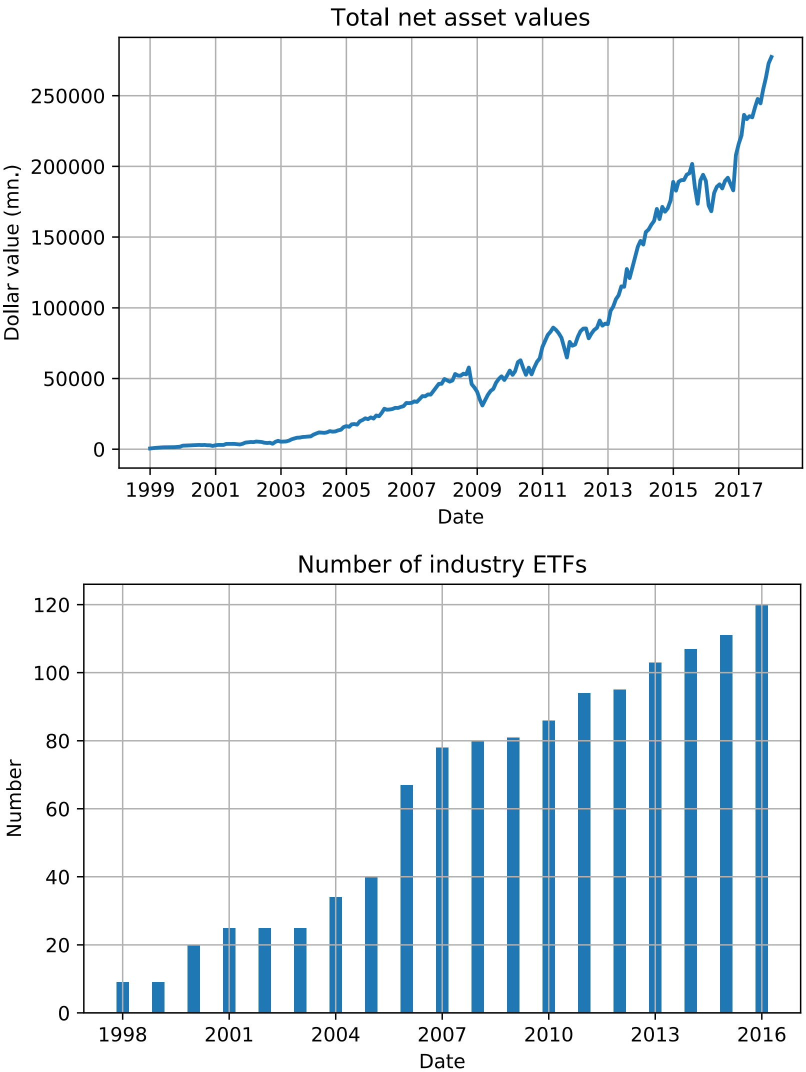

Figure 1
Total net asset value and the number of industry ETFs in the sample
This figure shows the time-series pattern of total net asset value and the number of industry ETFs from December 16, 1998 (the earliest inception date among our industry ETFs), to December 31, 2017 (the end of our sample period).

each ETF in each month, we define the short interest ratio (*SIR*) as short interest over total shares outstanding at the month end. Since *SIR* on the ETF can potentially be greater than 100%, particularly on industry ETFs, we follow the code from Prof. Byoung-Hyoun Hwang and replace *SIR* with 100% if it is higher than 100%.[9] While this truncation does not affect the results based on *SIR* ranking, it mitigates the effect of outliers in the regressions. In fact, all our results remain unchanged if we use the original value of *SIR*.

2.2 Firm-level data

2.2.1 Data on earnings announcements. We construct our data on earnings announcements from COMPUSTAT and financial market data from CRSP. We focus on quarterly earnings announcements that are available in both COMPUSTAT and I/B/E/S. Following Livnat and Mendenhall (2006), we impose the following restrictions:

1. Ordinary common shares listed on the NYSE, AMEX, or NASDAQ.
2. The earnings announcement date is reported in both COMPUSTAT and I/B/E/S, and the reporting dates in COMPUSTAT and I/B/E/S differ by no more than one calendar day.
3. The price-per-share of the fiscal quarter end is available from COMPUSTAT and is greater than \$1.
4. The market value of equity at the fiscal quarter end is available and is larger than \$5 million.
5. Daily stock returns are available in CRSP for dates around the earnings announcement.

We follow Livnat and Mendenhall (2006) and define earnings surprises as the standardized unexpected earnings (*SUE*) following a rolling seasonal random walk model. The *SUE* of firm i at quarter t is calculated as $SUE_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-4}}{P_{i,t}}$, where $EPS_{i,t}$ is the earnings per share at quarter t and $P_{i,t}$ is the price per share of firm i at the end of quarter t from COMPUSTAT.[10] In the Internet Appendix, we consider an alternative analyst-forecast-based measure of earnings surprises and find similar results.

2.2.2 Hedge fund holdings. The data on hedge fund stock holdings are constructed by manually matching Thomson Reuters 13F institutional holdings data with a list of hedge fund company names. Under the Securities Exchange Act of 1934, all institutions with more than \$100 million assets under management (AUM) are required to report their stock holdings to the SEC through Form 13F filings, which include equity long positions worth over \$200,000 or more than 10,000 shares. The list of hedge funds is compiled from Form ADV filings (an SEC regulatory filing), Lipper TASS, and Morningstar

9 The code is from http://www.bhwang.com/txt/Short-Interest-Data-Code.txt.

10 We construct *SUE* based on the code from WRDS: https://wrds-web.wharton.upenn.edu/wrds/support/Data/_003 Sample%20Programs/Compustat/sue.cfm.

CISDM. Since 13F holdings data do not indicate which institutions are hedge funds, we follow Jiang (2019) to identify hedge funds through the following steps. First, from 2011 to 2017, we identify fund advisers from the amended Form ADV filings. After passage of the Dodd-Frank Act in 2010, all U.S. hedge fund advisers with more than $150 million in assets under management are required to file Form ADV. To filter out advisers whose major line of business is not hedge fund management, we identify an adviser as a hedge fund if 80% of its assets are in the hedge fund business.[11] Second, to complement the list of hedge funds in the first step, we follow Griffin and Xu (2009) and add a list of hedge funds from two commercial hedge funds databases (Lipper TASS and Morningstar CISDM). Third, to focus on equity hedge funds, we drop hedge funds with a self-reported investment strategy of fixed income, global macro, real estate, or fund of funds. Last, we manually merge hedge funds identified in the previous steps with Thomson Reuters 13F data via company names. The final sample includes 751 unique hedge funds.[12]

2.2.3 Measuring *long-the-stock/short-the-ETF* activity. We construct a dummy variable, denoted *Dummy_LS*, to measure the *long-the-stock/short-the-ETF* activity on one stock using its parent ETF. Specifically, consider an industry ETF and one of its constituent stocks as a pair. For each ETF-stock pair in a given quarter, we set *Dummy_LS* equal to one if both the abnormal hedge fund holdings of this stock (*AHF*) and the abnormal short interest ratio of this ETF (*ASIR*) are above their 80th percentiles in the sample; otherwise, *Dummy_LS* is set to zero. We follow Chen, Da, and Huang (2019) and define *AHF* as the number of shares of this stock held by hedge funds at a given quarter end minus the average number of shares held by hedge funds in the past four quarters, divided by the number of shares outstanding at the quarter end. *ASIR* is defined as the short interest ratio of the ETF at a given quarter end minus the average short interest ratio of the ETF in the past four quarters. In short, *Dummy_LS* captures whether there are simultaneous spikes in hedge fund trading on this stock and short interest in its parent ETF.

[11] This criterion is in the same spirit of Brunnermeier and Nagel (2004), Griffin and Xu (2009) and Chen, Da, and Huang (2019) (using 50% cutoff) but is more conservative.

[12] We thank Prof. Wenxi Jiang for sharing the data on hedge funds. There are two potential caveats due to the exemption of registration. First, prior to the Dodd-Frank Act, hedge funds were exempted from the Investment Advisers Act. Second, even after the Dodd-Frank Act, funds with assets under managements less than $150 million have an exemption. In this sense, the list of hedge funds might not be complete. Hedge funds identified in our approach tend to be large ones or were alive until 2011. Nevertheless, we compare the distribution of abnormal hedge fund holdings to those of prior studies (e.g., Chen, Da, and Huang 2019) and find they have similar distributions. For example, while the mean (standard deviation) of our abnormal hedge fund holdings is 0.21 (1.92), the mean (standard deviation) is 0.20 (2.10) in Chen, Da, and Huang (2019). These similar distributions support our use of this hedge fund list. In addition, the list incompleteness is less concerned given that we can only obtain holdings data from 13F filings, which cover institutions with more than $150 million AUM. Meanwhile, since we use dummy variables to measure the spike in changes in hedge fund holdings to measure long-short activity, these two caveats will not severely bias our results.

Table 1
Summary statistics for the sample

A. Industry ETFs

	Mean	Std.	5%	25%	50%	75%	95%
SIR	0.115	0.209	0.001	0.007	0.022	0.112	0.594
log(Shrout)	15.694	1.682	12.812	14.670	15.703	16.781	18.455
Price	53.919	34.132	16.875	29.637	47.242	67.529	118.782
log(Dollar volume)	13.879	2.347	10.255	12.297	13.756	15.116	18.273
log(TNA in $ millions)	5.660	1.769	2.588	4.516	5.771	6.849	8.621

B. Nonindustry ETFs

	Mean	Std.	5%	25%	50%	75%	95%
SIR	0.037	0.111	0.000	0.003	0.007	0.019	0.170
log(Shrout)	15.487	1.834	12.612	14.197	15.278	16.797	18.689
Price	58.196	37.599	16.315	29.497	49.793	76.727	129.401
log(Dollar volume)	12.992	2.342	9.715	11.418	12.663	14.337	17.103
log(TNA in $ millions)	5.511	2.105	2.351	3.978	5.249	6.864	9.349

C. Earnings announcement sample

	Mean	Std.	5%	25%	50%	75%	95%
SUE	−0.001	0.060	−0.071	−0.006	0.001	0.007	0.064
AHF	0.212	1.920	−2.639	−0.257	0.000	0.478	3.842
Size	19.790	2.002	16.755	18.291	19.654	21.121	23.321
BM	0.686	0.589	0.107	0.303	0.538	0.874	1.783
Momentum	0.084	0.378	−0.467	−0.133	0.047	0.236	0.775
EarnPerst	0.260	0.361	−0.265	−0.013	0.213	0.521	0.898
# analysts	3.983	5.452	0.000	0.000	2.000	5.000	16.000

Panels A and B report the summary statistics on the quarterly short interest ratio (*SIR*), the natural logarithm of shares outstanding, of volume, of total net asset value (*TNA*), and price for industry and nonindustry ETFs, respectively. The quarterly measure in panels A and B is constructed by taking the average of monthly observation. Panel C reports the summary statistics for stocks in our earnings announcement sample. We follow Livnat and Mendenhall (2006) and compute *SUE* (the standardized earnings surprise) from a rolling seasonal random walk model. *AHF* is the number of shares of one stock held by hedge funds at quarter end minus the average number of shares of this stock held by hedge funds in the past four quarters, divided by the number of shares outstanding at quarter end. *Size* is the natural log-transformed market capitalization. *BM* is book-to-market ratio where the book value is measured as the preceding fiscal year, and market value is measured as of the end of that calendar year. *Momentum* is the cumulative raw return over the 12-month period ending 1 month before the announcement month. *EarnPerst* is the earnings persistence as of the first-order autoregressive coefficient of quarterly earnings over the past 4 years. *# analysts* is the number of analysts.

2.3 Basic statistics

Table 1 compares the *SIR* of industry and nonindustry ETFs. We make two observations. First, on average, the *SIR* of industry ETFs is higher than that of nonindustry ETFs (11.5% vs. 3.7%). Second, the *SIR* of industry ETFs has a much longer right tail. Industry ETFs have an *SIR* of 59.4% at the 95th percentile, whereas nonindustry ETFs have an *SIR* of less than 20% at the same percentile.[13] Further comparison between industry and nonindustry ETFs is also shown in Figure 2. For industry ETFs, we observe a significant concentration of *SIR* at the 100% level (we replace *SIR* with 100% when it is higher than 100%). Such a pattern is not observed among nonindustry ETFs.

13 It is not due to the difference of the shares outstanding between industry and nonindustry ETFs (see panels A and B in Table 1) or the difference of *SIR* between their member stocks (see Internet Appendix Table A.1).

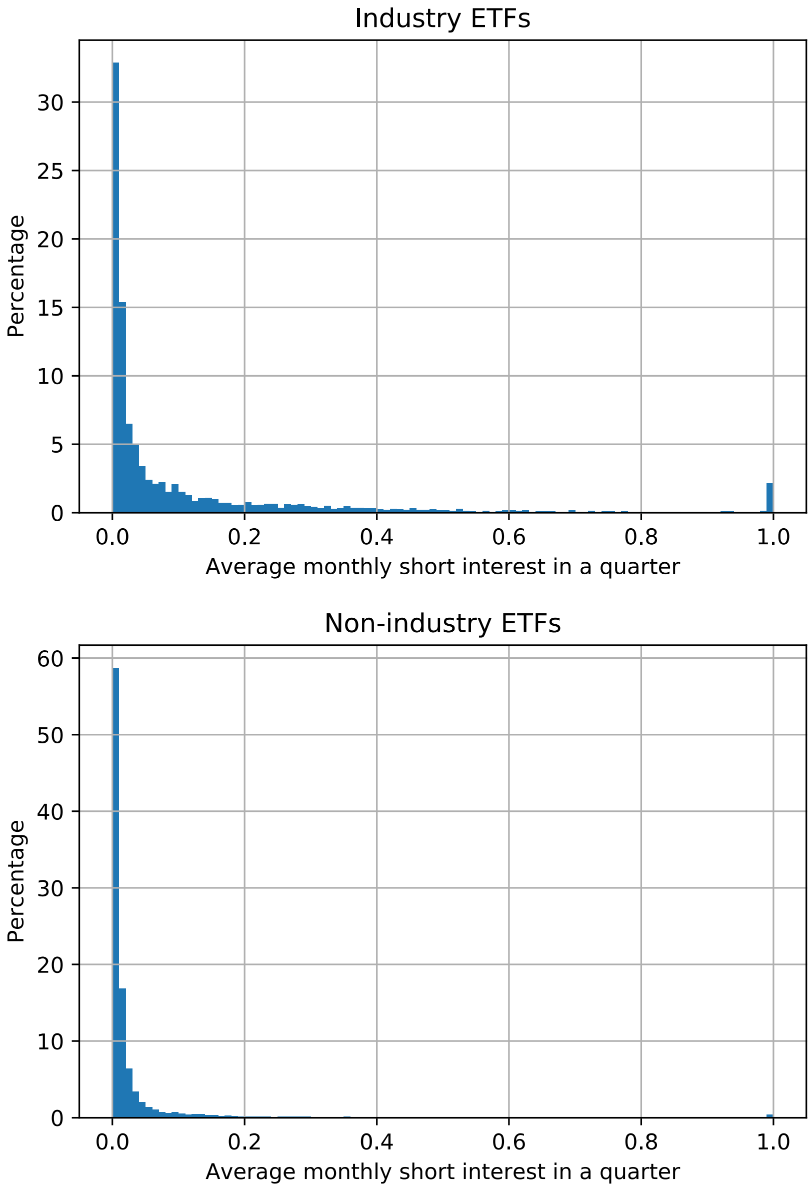

Figure 2
Histogram of the short interest ratio
This figure is a histogram of the short interest ratio of industry (top panel) and nonindustry ETFs (bottom panel), respectively. The short interest ratio is sampled quarterly using the average monthly ratio in a quarter.

The long right tail of *SIR* for industry ETFs confirms the Bloomberg report that industry ETFs are heavily shorted (see Internet Appendix Figure A.1).

3. Main Results

Can industry ETFs facilitate informed trading and enhance market efficiency? In this section, we investigate this question by focusing on the hedging-based *long-the-stock/short-the-ETF* activity. We first examine whether industry ETFs are involved in informed trader long-short activity prior to the announcement of positive earnings surprises. We then turn to exploring the implications of industry ETFs on market efficiency in the context of post-earnings-announcement drift (PEAD) and arbitrage risk.

3.1 Long-short activity: Hedge fund trading and industry ETF short interest

As noted previously, if informed investors use a *long-the-stock/short-the-ETF* strategy, we would expect informed investors' trading on stocks and short interest in the stock's parent industry ETF to spike simultaneously (*long-the-stock/short-the-ETF* activity) prior to the announcement of positive firm-specific news. Motivated by practitioner reports that hedge funds actively short industry ETFs, we combine hedge fund holdings on stocks and short interest in industry ETFs to capture such long-short activity.

To examine whether such a long-short activity exists, we focus on earnings announcements. There are several advantages to using earnings announcements. First, earnings surprise precisely indicates the direction of informed trading. Second, the earnings announcement date provides clear timing for informed trading. Third, PEAD can help clarify the market efficiency implication of the *long-the-stock/short-the-ETF* activity.

To examine long-short activity before earnings announcements, we focus on the sample of pairs of industry ETFs and member stocks. We follow Chen, Kelly, and Wu (2020) and run the following regression:

$$\begin{aligned} Dummy\_LS_{i,s,t} = {} & \beta_1 Dummy\_Pos\_SUE_{s,t} + Controls + Year\ FE \\ & + Quarter\ FE + ETF\ FE + Industry\ FE + \varepsilon_{i,s,t}, \end{aligned} \tag{1}$$

where $Dummy\_Pos\_SUE_{s,t}$ is a dummy variable and measures the earnings information of industry ETF i's member stock s at quarter t. It is equal to one if the stock's *SUE* is in the top 25% of the earnings announcement sample (following the definition of Chen, Kelly, and Wu 2020) and is zero otherwise. *Dummy_LS* is the latest long-short activity prior to earnings announcements. Control variables include the natural logarithm of the market capitalization (*Size*), book-to-market ratio (*BM*), institutional ownership (*IO*), the past 1-month return (*Reversal*), the cumulative return in the past 12 months (*Momentum*), earnings volatility (*EarnVola*), and earnings persistence (*EarnPers*) prior to the earnings announcement. Year, quarter, ETF, and industry fixed effects are included. All standard errors are clustered by ETF and time.[14]

Table 2 reports the results. As shown in columns 1 and 2 of panel A, the coefficient of *Dummy_Pos_SUE* is positive and significant. In other words, we find that long-short activity on an ETF-stock pair spikes before the stock announces a positive earnings surprise. This finding is consistent with Hypothesis 1.

In column 3, we use non-hedge-fund trading as a placebo test; that is, we construct *Dummy_LS* using abnormal holdings from nonhedge funds. Since nonhedge funds are unlikely to use the long-short, we do not expect *Dummy_LS* based on non-hedge-fund holdings to tick up before the positive *SUE*. The results in column 3 confirm this conjecture with the coefficient of *Dummy_Pos_SUE* being insignificant.

In panel B of Table 2, we split our sample period into the crisis period (2006Q4 – 2008Q4) and the noncrisis period, and then run regression (1) for each period. While the results for the noncrisis period (column 1 of panel B) are largely consistent with those in panel A, the results for the crisis period (column

Table 2
Long-short activity and positive earnings surprises

A. Full sample

	Dummy_LS based on Hedge fund holdings		*Dummy_LS* based on Nonhedge fund holdings
DepVar:	[1]	[2]	[3]
Dummy_Pso_SUE	0.009***	0.007***	0.002
	(5.79)	(4.97)	(1.16)
Size		−0.007***	−0.007***
		(−6.90)	(−6.63)
BM		0.002	−0.004**
		(1.52)	(−2.62)
Reversal		0.048***	0.055***
		(8.27)	(7.01)
IO		0.001	0.011
		(0.09)	(0.86)
Momentum		0.007**	0.031***
		(2.20)	(3.41)
EarnVola		0.00	0.00
		(1.16)	(0.81)
EarnPers		−0.000	0.001
		(−0.21)	(0.42)
Year FE	Yes	Yes	Yes
Qtr FE	Yes	Yes	Yes
ETF FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
No. obs.	379,167	361,813	361,813
Adj. R^2	.0310	.0357	.0678

(*Continued*)

14 This regression aims to show long-short activity prior to earnings announcements and is analogous to prior studies (e.g., Chen, Kelly, and Wu 2020; Boehmer and Wu 2013) that examine investor trading activity before earnings announcements.

Table 2
Continued

B. Crisis versus noncrisis period

DepVar: *Dummy_LS*	*Noncrisis period* [1]	*Crisis period* [2]
Dummy_Pso_SUE	0.007***	0.002
	(4.58)	(1.40)
Size	−0.007***	−0.009**
	(−6.95)	(−2.95)
BM	0.003**	−0.000
	(2.25)	(−0.04)
Reversal	0.045***	0.053**
	(8.62)	(2.76)
IO	0.008	−0.021
	(1.01)	(−1.16)
Momentum	0.005**	0.003
	(2.00)	(0.38)
EarnVola	0.00	−0.000***
	(0.13)	(−3.91)
EarnPers	−0.001	0.005
	(−1.16)	(0.86)
ETF FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Qtr FE	Yes	Yes
No. obs.	361,813	67,887
Adj. R^2	.0357	.0956

Test the difference of the Dummy_Pos_SUE coefficients between the noncrisis and crisis periods:

Coefficient difference	0.004**
χ^2	4.59

This table reports regression results of long-short activity ($Dummy\_LS_{i,s,t}$) on the dummy variable indicating positive *SUE* ($Dummy\_Pos\_SUE_{s,t}$), and the regression model is as follows:

$$Dummy\_LS_{i,s,t} = \beta_1 Dummy\_Pos\_SUE_{s,t} + Controls + Year\ FE + Quarter\ FE + ETF\ FE + Industry\ FE + \varepsilon_{i,s,t},$$

For each industry ETF and stock pair (i,s), where stock s is a constituent of industry ETF i, $Dummy\_Pos\_SUE_{s,t}$ is a dummy that equals one if the quarterly earnings announcement of stock s has a positive earnings surprise (defined as the top 25% *SUE* in our sample), and it equals zero otherwise. The dependent variable, $Dummy\_LS_{i,s,t}$, captures *long-the-stock/short-the-ETF* activity on stock s using ETF i at the nearest quarter end before the earnings announcement. Specifically, it equals one for an ETF-stock pair in a given quarter, if both abnormal hedge fund holdings of stock s ($AHF_{s,t}$) and the abnormal short interest ratio of ETF i ($ASIR_{s,t}$) are above their 80th percentile values in the sample; otherwise, it equals zero. We define $AHF_{s,t}$ as the number of shares of stock s held by hedge funds at quarter end minus the average number of shares of stock s held by hedge funds in the past four quarters, divided by the number of shares outstanding of stock s at quarter end. $ASIR_{s,t}$ is defined as the short interest ratio of ETF i at quarter end minus the average short interest ratio of ETF i in the past four quarters. We control for log market capitalization (*Size*), book-to-market ratio (*BM*), institutional ownership (*IO*), the past 1-month return (*Reversal*), the cumulative return in the past 12 months (*Momentum*), earnings volatility (*EarnVola*), and earnings persistence (*EarnPers*) prior to the earnings announcement. Year, quarter, ETF, and industry fixed effects are included. Panel A reports the regression results in the full sample period (1999 to 2017). In column 3 of panel A, we conduct a placebo test where the dependent variable is redefined as a dummy variable that equals one if abnormal non-hedge-fund holdings of stock s is above the 80th percentile value and the abnormal short interest ratio of ETF is above the 80th percentile value. Panel B reports the regression results in the crisis period (from 2006Q4 to 2008Q4) and the noncrisis period separately. All standard errors are clustered by ETF and time. t-statistics are reported in the parentheses. $*p<.1$; $**p<.05$; $***p<.01$. We use the Wald test to test the equivalence of the coefficients of $Dummy\_LS_{i,s,t}$ between the two sample periods and report the test statistics at the bottom of panel B.

2 of panel B) are different. Specifically, in column 2 of panel B, the coefficient of *Dummy_Pos_SUE* is insignificant, suggesting that long-short activity does not correlate with the positive *SUE* in the crisis period. We also show that the difference in the coefficient of *Dummy_Pos_SUE* between the crisis and noncrisis period is statistically significant.[15]

There are two potential explanations for the lack of correlation between long-short activity and positive *SUE* in the crisis period. First, arbitrageurs have scarce capital (Chen, Da, and Huang 2019), which may have curtailed *long-the-stock/short-the-ETF* activity during the crisis. Second, given the dismal prospects of some industries, arbitrageurs may have shorted industry ETFs to bet against the industry. Note that we do not view these explanations as mutually exclusive. Since we do not find evidence for long-short activity during the crisis period, we focus on the noncrisis period throughout the following analysis.

Our focus on the *long-the-stock/short-the-ETF* activity in our main analysis is motived by Table 1 and practitioner reports that industry ETFs have high short interest. Furthermore, we would not expect the opposite strategy (*short-the-stock/long-the-ETF*) to work as well given the much higher shorting costs of stocks. Nevertheless, we examine this issue in the Internet Appendix. In Internet Appendix Table A.2, we construct a measure (*Dummy_SL*) based on the abnormal short interest in the stock and the abnormal hedge fund holdings on the stock's parent industry ETF. We find some positive correlation between *Dummy_SL* and negative *SUE*.

Next, we conduct cross-sectional studies to strengthen the evidence for *long-the-stock/short-the-ETF* activity. In Hypothesis 1.a, we conjecture that the relationship between *long-the-stock/short-the-ETF* and positive *SUE* is more pronounced among stocks with higher industry risk exposure. To test this hypothesis, we split stocks into two groups based on industry risk exposure and repeat regression (1) for each group.

We measure industry risk exposure following Hwang, Liu, and Xu (2019). First, for each stock in each quarter, we use the information from the previous four quarters to estimate the return correlation between a stock and its parent industry ETF as

$$ExRet\_Stk_t = \beta_1 ExRet\_IndETF_t + \beta_2 MktRf_t + \varepsilon_t, \tag{2}$$

where *ExRet_Stk* is the daily excess return of the stock, *ExRet_IndETF* is the daily excess return of its parent industry ETF, and *MktRf* is the daily market excess return. Second, the stock's industry risk exposure is measured by the coefficient of *ExRet_IndETF* multiplied by the standard deviation of *ExRet_IndETF*.

15 We conduct a further subsample analysis based on the short-sale ban (2008Q3) within the crisis period and find that the relations between long-short activity and positive earnings surprises are not significant for both the short-sale ban period and the non-short-sale ban period, which suggests that the result for the crisis period is not merely due to the short-sale ban.

Then, we sort stocks into quartiles based on industry risk exposure. Following Hwang, Liu, and Xu (2019), the top quartile is assigned to the group of high industry risk exposure. The rest are assigned to the group of low industry risk exposure. We then apply regression (1) to each group.

Table 3 reports the results: columns 1 and 3 are for the group of low industry risk exposure; columns 2 and 4 are for the group of high industry risk exposure. The correlation between *Dummy_LS* and *Dummy_Pos_SUE* on stocks with high industry risk exposure is more than double that on stocks with low industry risk exposure (0.010 vs. 0.004). The difference is statistically significant, providing strong support for Hypothesis 1a.

Overall, Tables 2 and 3 provide supporting evidence that informed investors use the *long-the-stock/short-the-ETF* strategy to exploit firm-specific information. We now examine the market efficiency implication.

3.2 Implications for market efficiency: Post-earnings-announcement drift

According to theoretical studies (e.g., Dow 1998; Goldstein, Li, and Yang 2014), when industry ETFs help investors immunize their portfolios against industry risk, it facilitates investors' trading on firm-specific information and should consequently improve market efficiency.

To examine the market efficiency implication, we focus on PEAD. Motived by the strong evidence of long-short activity among member stocks of industry ETFs, we expect that market efficiency improves among member stocks. Thus, for the first test, we directly test the effect of industry ETF membership on PEAD. As a second test, we apply a *diff-in-diff* analysis among member stocks comparing PEAD for member stocks with high and low industry risk exposure, before and after the inception of the industry ETF.

In the first test, we are aware that member stocks of the industry ETF can differ from nonmember stocks in information environments. For example, ETF member stocks may have higher institutional ownership, which is positively associated with market efficiency, as reflected by lower PEAD. Hence, we use a PSM approach to create a matched sample for member stocks of the industry ETF, controlling for stock characteristics related to market efficiency. Specifically, when a stock is included in an industry ETF for the first time, we match this member stock with a nonmember stock from the same industry with the nearest propensity score. The propensity score for each stock is estimated via a logit model in the pooled sample of member and nonmember stocks. In the logit model, the dependent variable is a dummy taking a value one for a member stock and zero otherwise. Independent variables include a comprehensive list of stock characteristics related to market efficiency: market capitalization (Llorente et al. 2002), book-to-market ratio (Kelly and Ljungqvist 2012), institutional ownership (Chen, Kelly, and Wu 2020), the number of analysts (Chen, Kelly, and Wu 2020), and idiosyncratic volatility (Chen, Kelly, and Wu 2020). Because large member stocks always fail to be matched with

Table 3
Industry risk exposure and long-short activity

	Industry risk exposure subsample			
DepVar: *Dummy_LS*	Low [1]	High [2]	Low [3]	High [4]
Dummy_Pos_SUE	0.007***	0.012***	0.004***	0.010***
	(4.72)	(3.80)	(3.37)	(2.75)
Size			−0.007***	−0.008***
			(−6.19)	(−6.28)
BM			−0.001	0.005
			(−0.70)	(1.59)
IO			0.043***	0.060***
			(8.54)	(5.67)
Reversal			0.008	0.010
			(1.06)	(0.68)
Momentum			0.007**	0.009
			(2.08)	(1.28)
EarnVola			0.050***	0.022*
			(5.05)	(1.76)
EarnPers			−0.000	−0.001
			(−0.11)	(−0.19)
ETF FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
No. obs.	298,652	80,515	284,541	77,271
Adj. R^2	.0299	.0397	.0345	.0457

Test of equivalence of Dummy_Pos_SUE coefficients in columns 3 and 4:

Coefficient difference:	0.006**
χ^2	3.89

This table reports regression results of long-short activity ($Dummy\_LS_{i,s,t}$) on the positive *SUE* dummy ($Dummy\_Pos\_SUE_{i,s,t}$) in the subsample classified by industry risk exposure. We sort all ETF-stock pairs in the sample of Table 2 into quartiles based on each ETF-stock pair's industry risk exposure. Pairs in the top quartile are assigned into the group with high industry risk exposure, and the remaining pairs are assigned into the group with low industry risk exposure. The industry risk exposure of an ETF-stock pair is computed as follows. For each ETF-stock pair in each quarter, we follow Hwang, Liu, and Xu (2019) and first estimate the industry ETF beta for each member stock using daily returns in our sample period based on the following regression model:

$$ExRet\_Stk_t = \beta_1 ExRet\_IndETF_t + \beta_2 MktRf_t + \varepsilon_t,$$

where $ExRet\_Stk_t$ is the daily excess return of the stock, $ExRet\_IndETF_t$ is the daily excess return of the parent industry ETF, and $MktRf_t$ is the daily excess return of CRSP value-weighted market return. After that, we define industry risk exposure for an ETF-stock pair as the product of the estimated β_1 and the standard deviation of $ExRet\_IndETF_t$. In each subsample classified by industry risk exposure, we run the same regressions as in Table 2. While columns 1 and 3 report results on the subsample with low industry risk exposure, columns 2 and 4 report results on the subsample with high industry risk exposure. All standard errors are clustered by ETF and time. t-statistics are reported in the parentheses. $*p<.1$; $**p<.05$; $***p<.01$. We use the Wald test to test the equivalence of the coefficients of $Dummy\_Pos\_SUE_{s,t}$ between columns 3 and 4 and report the test statistics at the bottom of the table.

other stocks, we focus on member stocks with market capitalization below the industry median in this analysis.

Table 4 reports the results, with the outcome of PSM in panel A. Before matching, member stocks have larger firm size, higher institutional ownership, and more analyst following. However, after matching, member and nonmember stocks have similar stock characteristics. Overall, we find that PSM have successfully control for firm characteristics related to market efficiency.

To examine the membership effect on PEAD, we run the following regression on the matched sample:

$$CAR(1,k)_{s,t} = \beta_1 SUE\_Rank_{s,t} + \beta_2 Dummy\_Member_{s,t} + \beta_3 SUE\_Rank_{s,t} \times Dummy\_Member_{s,t} + Controls + Year\ FE + Quarter\ FE + Industry\ FE + \varepsilon_{s,t}, \quad (3)$$

where *CAR(1,k)* is the cumulative size-adjusted return from the first to the kth post-earnings-announcement trading day (k=30 or 60).[16] *SUE_Rank* is the quintile ranking of *SUE* in our sample, which takes values of −2, −1, 0, +1, and +2. *Dummy_Member* is a dummy indicating if the stock belongs to an industry ETF. We use the interaction term, *SUE_Rank* × *Dummy_Member*, to capture the industry ETF membership effect on PEAD. We control for the natural logarithm of market capitalization (*Size*), book-to-market ratio (*BM*), institutional ownership (*IO*), the number of analysts (*# analysts*), and idiosyncratic volatility (*IVOL*) prior to earnings announcements. Industry, year, and quarter fixed effects are included. Standard errors are clustered by stock and announcement date.

Table 4
Regress PEAD on the industry ETF membership in the matched sample

A. Characteristics of the member and nonmember stocks

Variable	Pre-matching difference in characteristics Member	Nonmember	Diff	t-stat.
Size	19.8812	18.7928	1.0884	33.15
BM	0.6070	0.6248	−0.0178	−1.52
IO	0.5974	0.3095	0.2879	52.24
# analysts	3.4087	0.9257	2.4831	68.49
IVOL	0.0237	0.0321	−0.0084	−20.88

Variable	Post-matching difference in characteristics Member	Nonmember	Diff	t-stat.
Size	19.8812	19.8595	0.0217	1.15
BM	0.6070	0.6113	−0.0043	−0.31
IO	0.5974	0.5877	0.0098	1.40
# analysts	3.4087	3.3530	0.0557	1.20
IVOL	0.0237	0.0231	0.0006	1.46

	Post-matching industry risk exposure Std. of stock ret	Industry risk exposure
Member stock	0.0717	0.0234
Matched nonmember stock	0.0707	0.0085

(*Continued*)

16 The results are robust to using DGTW-adjusted returns or Fama-French three-factor-adjusted returns.

Table 4
Continued

B. Regression in the matched sample

	CAR(1,30)		*CAR*(1,60)	
DepVar:	[1]	[2]	[3]	[4]
SUE_Rank	0.007***	0.007***	0.011***	0.012***
	(12.73)	(12.70)	(14.03)	(14.11)
Dummy_Member	−0.002*	0.001	−0.013***	−0.005**
	(−1.79)	(0.79)	(−7.70)	(−2.35)
SUE_Rank × *Dummy_Member*	−0.004***	−0.004***	−0.007***	−0.007***
	(−6.09)	(−5.86)	(−7.26)	(−7.12)
Size		−0.008***		−0.012***
		(−10.64)		(−11.00)
BM		−0.003*		−0.002
		(−1.89)		(−1.01)
IO		0.019***		0.022***
		(8.77)		(6.85)
# analysts		0.001***		0.000
		(2.71)		(0.27)
IVOL		−0.196***		−0.466***
		(−2.60)		(−4.34)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Qtr FE	Yes	Yes	Yes	Yes
No. obs.	119,832	118,661	119,832	118,661
Adj. R^2	.0047	.0072	.0055	.0084

This table reports the results in the propensity score matching (PSM). When a stock is included in an industry ETF for the first time, we match this member stock with a nonmember stock from the same industry (Fama and French 12-industry classification) using the one-to-one nearest neighbor propensity score matching method. To estimate the propensity score for the industry ETF constituent, we estimate a logit model where the dependent variable is a dummy that equals one for the member stock and zero for the nonmember stock. Independent variables include log market capitalization, book-to-market ratio, institutional ownership, the number of analysts, and idiosyncratic volatility prior to the inclusion event. We focus on the member stock with a market capitalization below the median within the industry since a large stock in the industry ETF cannot be matched with a similarly large nonmember stock from the same industry. Using the earnings announcement event of the matched sample from 1999 to 2017, except for the crisis period (from 2006Q4 to 2008Q4), we examine the impact of the industry ETF membership on PEAD with the following regression model:

$$CAR(1,k)_{s,t} = \beta_1 SUE\_Rank_{s,t} + \beta_2 Dummy\_Member_{s,t} + \beta_3 SUE\_Rank_{s,t} \times Dummy\_Member_{s,t}$$
$$+ Controls + Year\ FE + Quarter\ FE + Industry\ FE + \varepsilon_{s,t},$$

$CAR(1,k)_{s,t}$ is the cumulative size-adjusted return from the first to the kth post-earnings-announcement trading day of the earnings announcement event. $SUE\_Rank_{s,t}$ is the quintile ranking of *SUE* in our sample, taking values of −2, −1, 0, +1, +2 from the lowest to the highest quintile. $Dummy\_Member_{s,t}$ is a dummy variable, which equals one for the member stock and zero for the matched nonmember stock. Panel A reports pre-matching and post-matching characteristics of the industry ETF member and nonmember stocks. Panel A also reports the standard deviation of weekly stock returns and industry risk exposure (the industry ETF beta multiplies the standard deviation of weekly industry ETF returns) of the member and matched nonmember stocks. Panel B reports regression results in the matched sample. We control for log market capitalization (*Size*), book-to-market ratio (*BM*), institutional ownership (*IO*), the number of analysts (*# analysts*), and idiosyncratic volatility (*IVOL*) prior to the earnings announcement. Industry, year, and quarter fixed effects are included. All standard errors are clustered by the stock and announcement date. t-statistics are reported in the parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

As shown in panel B of Table 4, while the coefficient of *SUE_Rank* is significantly positive, the coefficient of the interaction term, *SUE_Rank* × *Dummy_Member*, is negative and significant, indicating that member stocks have smaller PEAD than nonmember stocks for the same level of the earnings surprise.[17] These results are consistent with Hypothesis 2 that industry ETFs improve market efficiency.

We are aware that even for nonmember stocks, investors could also use industry ETFs to hedge industry risk. That said, nonmember stocks have lower industry risk exposure compared to member stocks. In panel A of Table 4, the only notable difference between member and nonmember stocks is on industry risk exposure. While member and nonmember stocks have a similar level of return volatility (0.0717 vs. 0.0707), member stocks have more industry risk exposure (0.0234 vs. 0.0085). This comparison suggests that the PEAD-reducing effect with industry ETF membership is at least partially due to better industry risk hedging with industry ETFs for stocks with high industry risk exposure.

Although the PSM approach successfully controls for well-known characteristics related to market efficiency, some potential omitted variables that determine not only the inclusion in the ETF but also market efficiency could still exist. To alleviate this concern, we focus on only member stocks and conduct a *diff-in-diff* analysis. Specifically, motivated by Table 3 where long-short activity is more pronounced among stocks with high industry risk exposure, we compare PEAD for stocks with high and low industry risk exposure, before and after the inception of the industry ETF.

In the *diff-in-diff* analysis, we use earnings announcements of member stocks in the 2-year window around the ETF inception date. We assign member stocks into the treatment and control groups based on their industry risk exposure. We estimate industry risk exposure using the daily return of the member stock and a pseudo-industry ETF portfolio in the year before the ETF inception. We construct the pseudo-industry ETF portfolio using the portfolio holdings of the ETF when it first reports. For each inception event, the member stocks in the top quartile of industry risk exposure are assigned to the treatment group; the remaining stocks are assigned to the control group. Then, we run the following regression:

$$\begin{aligned} CAR(1,k)_{s,t} = {} & \beta_1 SUE\_Rank_{s,t} \times Treat_{s,t} \times Post_{s,t} + \beta_2 SUE\_Rank_{s,t} \\ & \times Treat_{s,t} + \beta_3 SUE\_Rank_{s,t} \times Post_{s,t} + \beta_4 Treat_{s,t} \times Post_{s,t} \\ & + \beta_5 SUE\_Rank_{s,t} + \beta_6 Treat_{s,t} + \beta_7 Post_{s,t} + Controls \\ & + ETF\ FE + Industry\ FE + Year\ FE + Quarter\ FE + \varepsilon_{s,t}, \end{aligned} \tag{4}$$

[17] In untabulated results, we find that member stocks have lower PEAD following both positive and negative *SUE*, which is consistent with the results in Internet Appendix Table A.2. In Table A.2, we find there also exists *short-the-stock/long-the-ETF* activity prior to negative earnings surprises. Meanwhile, we notice that member stocks have slightly lower *CAR(1,30)* and *CAR(1,60)*. This phenomenon could be potentially explained by the risk-return trade-off. As shown in Table 7, industry ETFs reduce arbitrage risk on member stocks and thus investors require lower returns among member stocks. However, investigating this issue is beyond the scope of this paper.

where *Treat* and *Post* are dummy variables to indicate the treatment group and post-inception date, respectively. Control variables and standard error estimates are the same as in regression (3).

Table 5 reports the results. The coefficient of the triple interaction term, *SUE_Rank* × *Treat* × *Post*, is negative and significant which suggests that the inception of the industry ETF reduces PEAD more on member stocks with high industry risk exposure. Since we focus on member stocks in the analysis, the PEAD-reducing effect is unlikely due to omitted variables that determine ETF membership. Combined with the finding that long-short activity is more pronounced on stocks with high industry risk exposure, the difference in PEAD reduction between stocks with high and low industry risk exposure suggests that using the industry ETF as a hedging vehicle can facilitate informed trading and thus improve market efficiency.

The key identifying assumption in the *diff-in-diff* analysis is the "parallel trend" assumption that the treatment group has a similar trend to the control group in the absence of treatment (the industry-inception event). That is, the high and low industry exposure groups should have a similar trend in PEAD reduction if the industry ETF is not introduced. To investigate the identifying assumption, we estimate the treatment effects at different time periods as follows:

$$
\begin{aligned}
CAR(1,k)_{s,t} = & \sum_{j\in\{-2,-1,+1,+2\}} \beta_{1,j} SUE\_Rank_{s,t} \times Treat_{s,t} \times Yr(j)_{s,t} \\
& + \sum_{j\in\{-2,-1,+1,+2\}} \beta_{2,j} SUE\_Rank_{s,t} Yr(j)_{s,t} \\
& + \sum_{j\in\{-2,-1,+1,+2\}} \beta_{3,j} Treat_{s,t} \times Yr(j)_{s,t} \\
& + \sum_{j\in\{-2,-1,+1,+2\}} \beta_{4,j} Yr(j)_{s,t} + Controls + ETF\ FE \\
& + Industry\ FE + Year\ FE + Quarter\ FE + \varepsilon_{s,t}, \qquad (5)
\end{aligned}
$$

where *Yr(-2)*, *Yr(-1)*, *Yr(+1)*, and *Yr(+2)* are pre- and post-treatment indicators for whether time t is within 1 or 2 years before or after the treatment. The coefficients of the interaction terms *SUE_Rank* × *Treat* × *Yr(-2)* and *SUE_Rank* × *Treat* × *Yr(-1)* capture the difference in the PEAD-reducing effect between the treatment and control groups in the pre-inception period. The coefficients of *SUE_Rank* × *Treat* × *Yr(+1)* and *SUE_Rank* × *Treat* × *Yr(+2)* capture the difference in the post-inception period.

As shown in Table 6, in each year before the inception of the industry ETF, PEAD is not significantly different for member stocks with high and low industry risk exposure. More importantly, the member stocks with high industry risk exposure experience lower PEAD than those with low industry

Table 5
Industry ETF inception effect on PEAD

	CAR(1,30)		*CAR*(1,60)	
DepVar:	[1]	[2]	[3]	[4]
SUE_Rank × *Treat* × *Post*	−0.005***	−0.004***	−0.008***	−0.006***
	(−3.59)	(−2.95)	(−3.97)	(−3.43)
SUE_Rank × *Treat*	−0.000	−0.000	0.001	0.002
	(−0.18)	(−0.06)	(0.93)	(0.99)
SUE_Rank × *Post*	0.002***	0.003***	0.002**	0.003***
	(3.48)	(4.29)	(2.42)	(2.99)
Treat × *Post*	−0.022***	−0.025***	−0.038***	−0.040***
	(−8.26)	(−9.02)	(−10.10)	(−10.26)
SUE_Rank	0.003***	0.003***	0.005***	0.004***
	(5.97)	(5.25)	(6.59)	(5.94)
Treat	0.016***	0.018***	0.025***	0.031***
	(7.96)	(9.27)	(9.49)	(11.19)
Post	0.012***	0.012***	0.016***	0.017***
	(5.93)	(6.07)	(5.32)	(5.46)
Controls	No	Yes	No	Yes
ETF FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Qtr FE	Yes	Yes	Yes	Yes
No. obs.	199,048	189,325	199,048	189,325
Adj. R^2	.0128	.0167	.0115	.0174

This table reports the *diff-in-diff* analysis on the impact of the industry ETF inception on PEAD. The *diff-in-diff* sample focuses on the industry ETF inception event during our sample period. For an industry ETF inception event, we sort member stocks of the industry ETF into quartiles on their ex ante industry risk exposure. Ex ante industry risk exposure is computed using the daily return of the member stock and a pseudo-industry ETF portfolio in the year before the inception date. The pseudo-industry ETF portfolio is constructed using the portfolio holdings of the industry ETF when it first reports. In each inception event, member stocks in the top quartile with large ex ante industry risk exposure are assigned to the treatment group, and the remaining stocks are assigned to the control group. We then examine the impact of industry ETF inception on PEAD in the (-2 years, +2 years) window around the inception date. The regression model is as follows:

$$
\begin{aligned}
CAR(1,k)_{s,t} = {} & \beta_1 SUE\_Rank_{s,t} \times Treat_{s,t} \times Post_{s,t} + \beta_2 SUE\_Rank_{s,t} \\
& \times Treat_{s,t} + \beta_3 SUE\_Rank_{s,t} \times Post_{s,t} + \beta_4 Treat_{s,t} \times Post_{s,t} \\
& + \beta_5 SUE\_Rank_{s,t} + \beta_6 Treat_{s,t} + \beta_7 Post_{s,t} + Controls \\
& + ETF\ FE + Industry\ FE + Year\ FE + Quarter\ FE + \varepsilon_{s,t},
\end{aligned}
$$

$CAR(1,k)_{s,t}$ is the cumulative size-adjusted return from the first to the kth post-earnings-announcement trading day of the earnings announcement event. $SUE\_Rank_{s,t}$ is the quintile ranking of *SUE* in our sample, taking values of -2, -1, 0, +1, +2 from the lowest to the highest quintile. $Treat_{s,t}$ is a dummy that equals one for the treatment group and zero for the control group. $Post_{s,t}$ is a dummy that equals one for the post-inception period and zero for the pre-inception period. We control for log market capitalization, book-to-market ratio, institutional ownership, the number of analysts, and idiosyncratic volatility prior to the earnings announcement. ETF, industry, year, and quarter fixed effects are included. We run the regression model on our earnings announcements from 1999 to 2017, except for the crisis period (from 2006Q4 to 2008Q4). All standard errors are clustered by the stock and announcement date. t-statistics are reported in the parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

risk exposure in the post-inception period. This evidence suggests that the PEAD-reducing effect in the *diff-in-diff* analysis comes from the inception of the industry ETF rather than the time trend.

To complement the results in the *diff-in-diff* analysis, we compare the stock characteristics between the treatment and control groups and find that the two

Table 6
Industry ETF inception effect on PEAD: Time trend

	CAR(1,30)		*CAR*(1,60)	
DepVar:	[1]	[2]	[3]	[4]
$SUE\_Rank \times Treat \times Yr(-2)$	0.00	0.00	0.001	0.001
	(0.13)	(0.08)	(0.74)	(0.69)
$SUE\_Rank \times Treat \times Yr(-1)$	−0.001	−0.001	0.002	0.001
	(−0.37)	(−0.59)	(0.86)	(0.77)
$SUE\_Rank \times Treat \times Yr(+1)$	−0.006***	−0.005***	−0.008***	−0.007***
	(−5.52)	(−4.69)	(−5.12)	(−4.20)
$SUE\_Rank \times Treat \times Yr(+2)$	−0.003***	−0.002**	−0.004**	−0.003*
	(−2.69)	(−1.99)	(−2.16)	(−1.70)
$SUE\_Rank \times Yr(-2)$	0.002***	0.002***	0.003***	0.003***
	(3.19)	(2.87)	(4.25)	(3.91)
$SUE\_Rank \times Yr(-1)$	0.003***	0.003***	0.005***	0.005***
	(5.94)	(5.54)	(6.10)	(5.62)
$SUE\_Rank \times Yr(+1)$	0.006***	0.006***	0.007***	0.007***
	(8.21)	(8.35)	(7.25)	(7.13)
$SUE\_Rank \times Yr(+2)$	0.004***	0.004***	0.006***	0.007***
	(6.29)	(7.16)	(6.30)	(6.97)
$Treat \times Yr(-2)$	0.018***	0.019***	0.029***	0.033***
	(4.09)	(4.37)	(4.78)	(5.38)
$Treat \times Yr(-1)$	0.012***	0.015***	0.005	0.010
	(2.58)	(3.13)	(0.80)	(1.52)
$Treat \times Yr(+1)$	0.006	0.003	−0.000	−0.001
	(1.51)	(0.87)	(−0.07)	(−0.11)
$Treat \times Yr(+2)$	0.010**	0.005	0.009	0.008
	(2.35)	(1.33)	(1.62)	(1.38)
$Yr(-2)$	−0.008	−0.007	−0.011	−0.010
	(−1.16)	(−0.94)	(−1.14)	(−0.94)
$Yr(-1)$	−0.010	−0.010	−0.005	−0.005
	(−1.43)	(−1.30)	(−0.49)	(−0.51)
$Yr(+1)$	−0.000	−0.001	0.012	0.010
	(−0.02)	(−0.17)	(1.20)	(0.96)
$Yr(+2)$	0.006	0.003	0.019*	0.013
	(0.79)	(0.42)	(1.77)	(1.14)
Controls	No	Yes	No	Yes
ETF FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Qtr FE	Yes	Yes	Yes	Yes
No. obs.	186,480	180,545	186,480	180,545
Adj. R^2	.0136	.0168	.0133	.0175

This table reports the dynamics of treatment effects of the *diff-in-diff* analysis in Table 5. In this table, we use the sample from Table 5 and further require all firms to have eight quarterly observations before and after ETF inception dates. We generate four event time dummies ($Yr(j)$, where j takes values of $(-2, -1, 1, 2)$ to indicate the event year of each observation. For example, $Yr(+1)$ is a dummy that equals one for observations in the first event year (365 calendar days) after the ETF inception date, and it equals zero elsewhere. Then we run the following regression to estimate the dynamics of treatment effects:

$$CAR(1,k)_{s,t} = \sum_j \beta_{1,j} SUE\_Rank_{s,t} \times Treat_{s,t} \times Yr(j)_{s,t} + \sum_j \beta_{2,j} SUE\_Rank_{s,t} \times Yr(j)_{s,t}$$

$$+ \sum_j \beta_{3,j} Treat_{s,t} \times Yr(j)_{s,t} + \sum_j \beta_{4,j} Yr(j)_{s,t} + Controls + ETF\ FE$$

$$+ Year\ FE + Quarter\ FE + Industry\ FE + \varepsilon_{s,t},$$

$CAR(1,k)_{s,t}$ is the cumulative size-adjusted return from the first to the kth post-earnings-announcement trading day of the earnings announcement event. $SUE\_Rank_{s,t}$ is the quintile ranking of *SUE* in our sample, taking values of -2, -1, 0, +1, +2 from the lowest to the highest quintile. $Treat_{s,t}$ is a dummy that equals one for the treatment group and zero for the control group. $Post_{s,t}$ is a dummy that equals one for the post-inception period and zero for the pre-inception period. We control for log market capitalization, book-to-market ratio, institutional ownership, the number of analysts, and idiosyncratic volatility prior to the earnings announcement. ETF, industry, year, and quarter fixed effects are included. We run the regression model on our earnings announcements from 1999 to 2017, except for the crisis period (from 2006Q4 to 2008Q4). All standard errors are clustered by the stock and announcement date. t-statistics are reported in the parentheses. $^*p<.1$; $^{**}p<.05$; $^{***}p<.01$.

groups have similar firm characteristics related to market efficiency (see Internet Appendix Table A.3).

In brief, Tables 4 to 6 support our argument that industry ETFs improve market efficiency. Taken together with the results in Tables 2 and 3, our analysis shows that using industry ETFs as a hedging vehicle can facilitate informed trading and thus improve market efficiency.

3.3 Implications for arbitrage risk

In this subsection, we provide further evidence to show that industry ETFs improve market efficiency. Specifically, we examine how industry ETFs affect arbitrage risk on stocks. If industry ETFs indeed facilitate informed investors' arbitrage activity among their member stocks, then member stocks should experience decreases in arbitrage risk.

We use the methodology of Wurgler and Zhuravskaya (2002) to calculate arbitrage risk for each stock in each year. This arbitrage risk measures to what extent a stock's return variation can be hedged by its substitute stocks. For a subject stock at each year end, we find three substitute stocks that most closely match the subject stock with respect to industry, size, and book-to-market ratio. The arbitrage risk of the subject stock in a given year is the residual variance in the regression of daily excess returns of the subject stock on those of the substitutes in the year (for details, see Wurgler and Zhuravskaya 2002).

We then conduct a *diff-in-diff* analysis to determine how the inception of the industry ETF exerts different effects on the arbitrage risk of member stocks and nonmember stocks. For each industry ETF inception event, we assign member stocks into the treatment group and assign nonmember stocks from the same Fama-French 12 industry in which the industry ETF resides into the control group. Moreover, for each inception event, we require nonmember stocks to not be held by any industry ETF in the (-2 years, +2 years) window around the inception date.

Table 7 reports the result, where *Treat* and *Post* are dummy variables that indicate the treatment group and the post-inception period, respectively. Control variables and standard error estimates are the same as in regression (4). We also control for ETF, industry, and year fixed effects. The interaction term of *Treat* and *Post* is negative and significant, providing direct evidence that the inception of the industry ETF leads to a meaningful reduction in arbitrage risk.

We further explore the mechanism for the reduction in arbitrage risk with the inception of the industry ETF. Specifically, we attempt to provide evidence that industry ETFs are selected as substitutes for the member stock's pair stocks (e.g., stocks in the same industry) as the hedging vehicle in arbitrage trading. We utilize the cross-sectional difference in the shorting difficulty of pair stocks relative to the industry ETF. For member stocks whose pair stocks are more difficult to short relative to the industry ETF, hedging with the industry ETF is more effective; thus, *long-the-stock/short-the-ETF* activity should be more pronounced for these stocks. This is indeed what we find (see Internet

Table 7
Industry ETF inception effect on arbitrage risk

	Arbitrage risk (%)	
DepVar:	[1]	[2]
Treat × *Post*	−0.020**	−0.012***
	(−2.37)	(−3.28)
Treat	0.024***	0.006*
	(3.78)	(1.37)
Post	0.000	−0.004
	(0.06)	(−0.67)
Control	No	Yes
ETF FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
No. obs.	81,883	81,883
Adj. R^2	.112	.226

This table reports the ETF inception effect on arbitrage risk through a *diff-in-diff* analysis. We measure the annual arbitrage risk for each stock following Wurgler and Zhuravskaya (2002). Specifically, for a subject stock at a year end, we find three substitute stocks that match the subject stock on Fama-French 48 industry and as closely as possible on size and book-to-market ratio (see Wurgler and Zhuravskaya 2002) for details about this procedure). The arbitrage risk of the subject stock in a given year is the residual variance in the regression of daily excess returns of the subject stocks on those of the substitutes in the year. We then conduct a *diff-in-diff* analysis on how the inception of industry ETFs exerts different effects on member stocks and nonmember stocks. For each industry ETF inception event, we assign member stocks into the treatment group and assign nonmember stocks from the same Fama-French 12 industry as the industry ETF into the control group. Moreover, for each inception event, we require nonmember stocks not to be held by any industry ETF in the (−2 years, +2 years) window around the inception date. Then we track the annual arbitrage risk of treatment and control stocks in the −2/−1/+1/+2 years relative to the year of inception. The *diff-in-diff* sample consists of industry ETF inception events in the period from 1999 to 2017, except for the crisis period (from 2006Q4 to 2008Q4). *Treat* is a dummy that equals one for treatment stocks, and *Post* is a dummy that equals one for post-inception years. We control for size, book-to-market ratio, institutional ownership, the number of analysts following, and idiosyncratic volatility. ETF, industry, and year fixed effects are included. All standard errors are clustered by stock and year. t-statistics are reported in the parentheses. $*p<.1$; $**p<.05$; $***p<.01$.

Appendix Table A.6.1), which suggests that industry ETFs provide a hedging vehicle for arbitrageurs and thus facilitate arbitrage activity, leading to lower arbitrage risk.[18]

In sum, our findings on arbitrage risk and substitution between the industry ETF and pair stocks as the hedging vehicle provide further support for our argument that industry ETFs improve market efficiency.

4. Robustness Checks and Additional Analysis

In Section 3, we provide evidence to support our hypotheses that industry ETFs provide a hedging benefit to informed investors and thus improve market efficiency. In this section, we conduct additional tests to corroborate our evidence. First, we perform various robustness checks, including alternative definitions of key variables (e.g., long-short activity and earnings surprises),

[18] We also examine how the inception of the industry ETF affects the return correlation among member stocks and find that the industry ETF increases the return correlation among its member stocks (see Internet Appendix Table A.4). This suggests that industry ETFs facilitate investors' arbitrage and thus help correct mispricing arising from firms' idiosyncratic components, which effectively decreases firm-specific noises and increases the return correlation.

industry ETFs, and industry risk exposure. Second, we use nonindustry ETFs as a placebo test. Third, we conduct additional cross-sectional studies based on the shorting cost of industry ETFs. To be concise, we highlight the main results in this section and leave the detailed description of the empirical implementation to the Internet Appendix.

4.1 Robustness checks on long-short activity and positive *SUE*

First, we consider alternative measures of the key variables, including *Dummy_LS* and *SUE*. Regarding *Dummy_LS*, we consider alternative cutoffs (e.g., the 75th or 85th percentile value in the sample) of abnormal hedge fund holdings of a stock and the abnormal short interest ratio of the stock's parent ETF to define long-short activity. Regarding *SUE*, we follow Livnat and Mendenhall (2006) and define earnings surprises based on analyst forecasts. The results in Table 2 are robust (see Table A.5.1).

Second, we use alternative ways to identify industry ETFs. Specifically, we consider alternative cutoffs (e.g., 25% or 40%) for the weight of the dominant industry in an industry ETF's portfolio; we remove the requirement of at least 30 stocks in the portfolio; and we consider a tighter requirement that the ETF contain at least 30 stocks in the industry. The findings in Table 2 are unchanged (see panel B of Table A.5.1).

Third, we apply an alternative regression specification to examine the correlation between long-short activity and positive earnings surprises. That is, we regress member stock's abnormal hedge fund holdings (*AHF*), on the parent ETF's *SIR*, *Dummy_Pos_SUE* of the stock, and their interaction term. The interaction term captures the correlation between *AHF* and *SIR* conditional on *Dummy_Pos_SUE*. The interaction term is positive and significant, which is consistent with our main findings that long-short activity surges before positive *SUE* (see Table A.5.2).

4.2 Robustness checks on market efficiency

Following the above, we reexamine our *diff-in-diff* analysis in Table 5 with various alternative identifications of industry ETFs and with the analyst-based *SUE*. As reported in Table A.5.3, the PEAD-reducing effect remains the same across all tests.

We also directly regress PEAD on long-short activity and find that long-short activity reduces PEAD. However, given the correlation between long-short activity and earnings surprises (see Table 3), we are conservative in using this test as the main analysis and thus report the results in Table A.5.4.

In addition, in Table A.5.5, we use nonindustry ETF membership as a placebo test and find that nonindustry ETF membership is not associated with the PEAD-reducing effect. In contrast, even before PSM, we find that industry ETF membership is associated with a PEAD-reducing effect (see columns 1 and 2 in Table A.5.5). This sharp contrast between the effects with industry and nonindustry ETF membership highlights the uniqueness of industry ETFs in improving market efficiency.

4.3 An alternative definition of industry risk exposure

We follow Hwang, Liu, and Xu (2019) and consider an alternative definition of industry risk exposure. Specifically, we use the estimate of the industry ETF beta (β_1) in regression (2) to measure member stocks' industry risk exposure and repeat the analysis in Table 3 and Table 5. As shown in Tables A.5.6 and A.5.7, all results remain unchanged.

4.4 Other cross-sectional studies

4.4.1 Substitution between pair stocks and the industry ETF. Our main hypothesis is that informed investors use industry ETFs to hedge industry risk. In addition to industry ETFs, investors could use stocks in the same industry (e.g., pair stocks) to hedge industry risk. In this sense, pair stocks and industry ETFs are substitutes. To what extent the latter is more efficient than the former depends on the relative shorting costs. For example, for a given stock, if its pair stocks have higher shorting costs relative to the industry ETF, shorting the industry ETF is more cost effective. Hence, for this stock, we expect more pronounced *long-the-stock/short-the-ETF* activity.

To test this argument, we split stocks based on their pair stocks' relative shorting cost (to the industry ETF) into low and high groups and conduct a cross-sectional analysis similar to the test based on industry risk exposure. We measure the shorting cost as the daily cost of borrowing score (DCBS metric) from the Markit database. As reported in Table A.6.1, we find that long-short activity is significantly and positively associated with the positive *SUE* only for ETF member stocks whose pair stocks are relatively difficult to short. This finding supports our argument that hedging with industry ETFs is most cost effective when shorting pair stocks is expensive. Moreover, the PEAD-reducing effect is concentrated on stocks whose pair stocks have relatively high shorting cost (see Table A.6.2).

4.4.2 Cross-sectional studies based on the shorting cost of the industry ETF. Given that a stock can belong to multiple industry ETFs, we utilize the cross-sectional variation in the industry ETF shorting cost to provide insights into long-short activity and the implications for market efficiency. We split industry ETFs into two groups based on the sample median of the shorting cost of the industry ETF. As a low shorting cost facilitates the *long-the-stock/short-the-ETF* strategy, we hypothesize that long-short activity and the PEAD-reducing effect are more pronounced in stocks whose parent industry ETFs have lower shorting costs. Tables A.7.1 and A.7.2 confirm our conjecture.

Following a similar intuition, we propose that long-short activity should be easier to implement among stocks belonging to a larger set of industry ETFs, leading to lower PEAD among these stocks. The results in Table A.7.3 are consistent with this conjecture.

5. The Return Predictability of ETF Short Interest

Our findings in Sections 3 and 4 that investors use the hedging capability of industry ETFs to exploit positive firm-specific information and that this activity improves market efficiency have important asset pricing implications. In this section, we study these asset pricing implications for the return predictability of industry ETFs and their member stocks.

5.1 Return predictability and short interest

Intuitively, when informed investors hedge by shorting an industry ETF, they do so because they have positive information on an underlying stock (or stocks). Thus, hedging-related short interest in the ETF is actually a positive signal, in contrast to the standard negative news conveyed by short positions, about these underlying prospects. Since the ETF will eventually incorporate the positive information of the member stocks, this suggests that short interest in an industry ETF should positively predict the future return on the ETF. We note at the outset that this assumes the market cannot instantly infer such information and thereby adjust both the ETF and the underlying prices. This assumption is sensible since short interest can reflect both positive-news-based hedging demand and negative-news-based speculative demand, confounding inferences about its information content.

We first use a portfolio sorting approach to examine return predictability. Specifically, we follow prior studies on short selling (e.g., Jiao, Massa, and Zhang 2016; Desai et al. 2002) and use the monthly changes in the short interest ratio, ΔSIR, as the sorting variable. That is, we sort all industry ETFs into three groups based on their ΔSIR[19] Then, we construct an equal-weighted portfolio that longs the ETFs in the highest group and shorts the ETFs in the lowest group. We hold this portfolio for 1 month and conduct monthly rebalancing. In this test, we start our sample from 2005 due to the scarcity of the industry ETFs in the earlier period.

Notably, we sort on ΔSIR rather than the level of the short interest ratio (i.e., SIR) due to the high persistence feature of SIR among industry ETFs. In panel C of Table A.1, we sort the industry ETFs into quintiles based on SIR every month and find that an ETF in the top quintile in the current month has an approximately 90% likelihood of remaining in the top quintile in the next month. Therefore, we follow the standard approach in the literature (e.g.,

[19] We sort industry ETFs into three groups rather than deciles because of the limited number of industry ETFs in our sample, particularly in the early period. Also, in untabulated results, we consider an alternative ΔSIR, that is, the current SIR minus the average SIR in the past quarter or year and find similar results.

Jiao, Massa, and Zhang 2016; Chen, Da, and Huang 2019) and use ΔSIR in the return predictability test.

Table 8 reports the results. Panel A.1 shows that the long-short portfolio of industry ETFs sorted on ΔSIR generates a positive and significant Fama-French-Carhart four-factor (four-factor hereinafter) alpha of 25 bps ($t=2.59$) per month. To show that the return predictability is fundamentally driven, we examine how ΔSIR predicts the percentage change in the net asset value of the ETF (ΔNAV). In panel A.2, when we replace ETF returns with ΔNAV in the portfolio sorting, we find that ΔSIR also positively predicts ΔNAV with a significant four-factor alpha of 28 bps ($t=2.81$) in the long-short portfolio. These results are robust to controlling for fundamental characteristics in the Fama-MacBeth regressions (see panel C). Given the large amount of evidence showing that *SIR* negatively predicts returns at the stock level (e.g., Diether, Lee, and Werner 2009), our finding is surprising, but it supports the hedging role of industry ETFs.[20]

There are several potential alternative explanations for the above return patterns. One explanation is that short sellers are simply trading in the "wrong" direction on industry ETFs. Since retail investors are mostly unsophisticated and thus tend to trade in the wrong direction, if short interest in industry ETFs largely comes from retail investors, we could observe positive return predictability of the industry ETF *SIR*. To address this concern, we follow Boehmer, Jones, and Zhang (2019) and calculate the retail order flow on industry ETFs. As shown in Internet Appendix Table A.8, the retail order flow is not significantly correlated with *SIR* on industry ETFs, which suggests that the positive return predictability is unlikely to be driven by trading from retail investors.[21]

Another concern for the difference in findings between our study (with a focus on ETFs) and prior studies (with a focus on stocks) is that the member stocks of the industry ETF differ from the stocks used in prior studies. To address this concern, we focus on member stocks of the industry ETF and examine how the stock-level ΔSIR predicts the stock return. We find that even among these member stocks, the stock-level ΔSIR negatively and significantly predicts the stock return, which is consistent with prior studies on stocks (see panel B of Table 8).

The positive return predictability of ΔSIR in the industry ETF may arise from the unique structure of ETFs. When an ETF is traded at a premium relative to the net asset value of its constituents, then arbitrageurs short the industry ETF

[20] The feature that industry ETFs have higher *SIR* than nonindustry ETFs (see Table 1 and Internet Appendix Table A.1) could explain the seeming contradiction between our finding and Li and Zhu (2019), who find a negative return predictability of *SIR* on *all* US equity ETFs. Li and Zhu (2019) focus on *all* US equity ETFs and use the *level* of *SIR* as the sorting variable.

[21] Short interest in industry ETFs could also come from other motives, for example, "operational shorting" arising from creation/redemption activities (Evans et al. 2018). However, these motivations could not fully explain our findings. For example, Evans et al. (2018) find that "operational shorting" is unrelated to future monthly ETF returns or changes in net asset value (see their table 7).

and long its member stocks to correct the mispricing. This arbitrage activity could result in contemporaneous price pressure on the industry ETF, which reverts in the future. Panel A.2 of Table 8 (forecasting Δ*NAV*) suggests that this explanation is unlikely.[22]

In Appendix Table A.9.1, we find that the return predictability of Δ*SIR* becomes negative (though insignificant) in the crisis period. This result is consistent with our previous findings of no correlation between long-short activity and positive *SUE* in the crisis period.

Table 8
Short interest and future returns

A.1. Performance of industry ETF portfolios sorted by ΔSIR, based on ETF returns

	Excess returns [1]		CAPM alpha [2]		FF3 alpha [3]		FFC4 alpha [4]	
	Estimate	*t*-stat.	Estimate	*t*-stat.	Estimate	*t*-stat.	Estimate	*t*-stat.
Bottom 30%	1.11	3.02	−0.31	−4.63	−0.25	−4.31	−0.23	−4.19
Mid 40%	1.30	3.71	−0.09	−1.19	−0.04	−0.60	−0.03	−0.43
Top 30%	1.37	3.78	−0.05	−0.54	0.00	0.02	0.02	0.17
Top - bottom	**0.26**	**2.81**	**0.26**	**2.77**	**0.25**	**2.69**	**0.25**	**2.59**

A.2. Performance of industry ETF portfolios sorted by ΔSIR, based on ETF NAV change

	Excess returns [1]		CAPM alpha [2]		FF3 alpha [3]		FFC4 alpha [4]	
	Estimate	*t*-stat.	Estimate	*t*-stat.	Estimate	*t*-stat.	Estimate	*t*-stat.
Bottom 30%	0.96	2.56	−0.47	−5.50	−0.42	−5.36	−0.40	−5.40
Mid 40%	1.10	3.08	−0.30	−2.85	−0.26	−2.64	−0.24	−2.60
Top 30%	1.24	3.41	−0.18	−1.78	−0.13	−1.37	−0.12	−1.25
Top - bottom	**0.28**	**2.84**	**0.29**	**2.96**	**0.28**	**2.89**	**0.28**	**2.81**

B. Member stock portfolios sorted by ΔSIR

	Excess returns [1]		CAPM alpha [2]		FF3 alpha [3]		FFC4 alpha [4]	
	Estimate	*t*-stat.	Estimate	*t*-stat.	Estimate	*t*-stat.	Estimate	*t*-stat.
1 (low)	1.25	3.15	0.36	1.47	0.01	0.09	0.06	0.38
2	1.28	3.52	0.45	2.12	0.13	0.84	0.18	1.27
3	1.27	3.83	0.52	2.60	0.22	1.53	0.26	1.82
4	1.33	4.11	0.59	3.07	0.28	2.24	0.29	2.39
5	1.20	3.63	0.50	2.29	0.16	1.12	0.18	1.31
6	1.31	4.13	0.61	3.05	0.28	2.38	0.31	2.67
7	1.34	3.95	0.59	2.81	0.25	1.97	0.29	2.21
8	1.11	3.16	0.33	1.51	0.02	0.13	0.04	0.30
9	0.92	2.50	0.10	0.48	−0.22	−1.40	−0.17	−1.14
10 (high)	0.85	1.97	−0.12	−0.50	−0.46	−2.46	−0.39	−2.16
High - low	**−0.40**	**−3.22**	**−0.47**	**−3.97**	**−0.47**	**−3.93**	**−0.45**	**−3.67**

(*Continued*)

22 We conduct three additional tests to rule out this possibility. First, panel A of Table A.9.2 shows that the return predictability of Δ*SIR* on the industry ETF does not revert in the long run. Second, in panel B of Table A.9.2, we show that Δ*SIR* does not predict the industry ETF's mispricing (price discount/premium against *NAV*), which is a common measure of arbitrage activity (e.g., Evans et al. 2018). Third, we control for the percentage change in ETF shares outstanding, which is an alternative proxy for ETF arbitrage activity (Brown, Davies, and Ringgenberg 2019), in Fama-MacBeth regressions and find that our results are unaffected (panel C of Table A.9.2).

Table 8
Continued

C. Fama-MacBeth regression

	Ret_{t+1} of industry ETFs		ΔNAV_{t+1} of industry ETFs			Ret_{t+1} of member stocks	
DepVar:	[1]	[2]	[3]	[4]		[5]	[6]
ΔSIR_t	0.030***	0.023***	0.035***	0.025**	ΔSIR_t	0.106***	−0.104***
(ETF-level)	(2.78)	(2.27)	(2.84)	(2.10)	*(stock-level)*	(−3.02)	(−2.87)
Intercept	0.013***	0.015	0.012***	0.010	*Intercept*	0.014***	0.023***
	(3.72)	(1.31)	(3.31)	(0.83)		(4.11)	(3.31)
Controls	No	Yes	No	Yes	*Controls*	No	Yes

This table reports results on the return predictability of the monthly change in the short interest ratio (ΔSIR). Panel A.1 reports the average monthly excess return, CAPM alpha, Fama and French three-factor (FF3) alpha, and Fama-French-Carhart four-factor (FFC4) alpha for each industry ETF portfolio formed based on the ETF-level ΔSIR. At the end of each month, all industry ETFs are sorted into three groups based on ΔSIR in that month. Then, we track the equal-weighted portfolio return over the next month. Average monthly alphas are computed from January 2005 to December 2017, excluding the crisis period (2006Q4 to 2008Q4). In panel A.2, we conduct the same portfolio analysis as in panel A.1 but replace ETF returns by the percentage *NAV* change, which is calculated as the monthly change in *NAV* scaled by *NAV* at the previous month end. Panel B reports results for member stocks. At the end of each month, all member stocks are sorted into deciles based on the stock-level ΔSIR in that month. Member stocks with prices below \$5 per share or in the bottom NYSE size decile at the portfolio formation date are excluded. Then, we track the equal-weighted portfolio return over the next month. The holding period in panel B is from January 1999 to December 2017, excluding the crisis period (from 2006Q4 to 2008Q4). t-statistics in panels A and B are computed based on standard errors with Newey-West correction of one lag, and the portfolio alphas are reported in percent. Panel C reports the time-series average of the slope coefficient from Fama and MacBeth (1973) cross-sectional regressions on returns (Ret_{t+1}) and monthly changes in the short interest ratio, ΔSIR, for industry ETFs and their member stocks, respectively. In columns 3 and 4 of panel C, the dependent variable is replaced by percentage *NAV* change (ΔNAV_{t+1}) of industry ETFs. For each industry ETF, we average the member stocks' characteristics and use the average as a control variable in our regression. In our control variables, we include stock characteristics as of month t end, including past 12-month returns, log market capitalization, book-to-market ratio, asset growth, operating profitability, gross profitability, investment growth, net issuance, accruals, and net operating assets. For the stock-level regressions, the control variable corresponds to each stock's own characteristics. In industry ETF regressions, the sample period is from January 2005 to December 2017, excluding the crisis period (from 2006Q4 to 2008Q4). In regressions on member stocks, the sample period is from January 1999 to December 2017, excluding the crisis period (from 2006Q4 to 2008Q4). All standard errors are with Newey-West correction of one lag. t-statistics are reported in the parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

5.2 Cross-sectional studies: Return predictability of the industry ETF short interest

We further reinforce our argument that the positive return predictability of ΔSIR is largely due to the *long-the-stock/short-the-ETF* activity using conditional tests. In particular, when the spike in the short interest in industry ETFs coincides with increased hedge fund holdings on the member stock, the short is highly likely to belong to the short-leg of long-short activity. In this sense, ΔSIR should have stronger return predictability on the industry ETF when the ETF's constituents simultaneously experience spikes in holdings by hedge funds.

To test our conjecture, we first construct a measure, *PosAHF*, as the ratio of the number of the member stocks with positive abnormal hedge fund holdings over the total number of member stocks of an industry ETF. Intuitively, *PosAHF* captures hedge funds' long activity on the member stocks of an ETF. Then, we double sort industry ETFs on ΔSIR and *PosAHF* (3×3 groups) and track the performance of the long-short portfolio sorted by ΔSIR for each *PosAHF* group.

Table 9
Short interest, hedge fund holdings, and future ETF returns

A. Portfolios sorted by ΔSIR *and* PosAHF

		ETF return (%)				ETF *NAV* change (%)			
		High *PosAHF*		Low *PosAHF*		High *PosAHF*		Low *PosAHF*	
	Portfolios by Δ*SIR*	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.	Coef.	*t*-stat.
Excess returns	Low	0.84	1.86	1.32	4.05	0.77	1.67	1.11	3.37
	High	1.35	3.13	1.32	4.02	1.26	2.90	1.21	3.72
	High - low	0.51	2.75	0.00	−0.02	0.49	2.50	0.10	0.70
CAPM alpha	Low	−0.74	−3.87	0.10	0.80	−0.86	−3.85	−0.13	−0.91
	High	−0.20	−0.91	0.05	0.40	−0.34	−1.41	−0.09	−0.71
	High - low	0.54	2.58	−0.05	−0.37	0.52	2.41	0.04	0.26
FF3 alpha	Low	−0.67	−3.89	0.15	1.21	−0.78	−3.90	−0.08	−0.55
	High	−0.13	−0.62	0.09	0.78	−0.26	−1.15	−0.06	−0.51
	High - low	0.54	2.52	−0.06	−0.45	0.53	2.39	0.02	0.12
FFC4 alpha	Low	−0.62	−3.53	0.15	1.17	−0.74	−3.68	−0.08	−0.56
	High	−0.10	−0.50	0.09	0.77	−0.22	−1.04	−0.06	−0.50
	High - low	0.52	2.34	−0.06	−0.44	0.51	2.28	0.02	0.15

(*Continued*)

Table 9
Continued
B. Fama-MacBeth regressions

	DepVar: Ret_{t+1}				DepVar: ΔNAV_{t+1}			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
ΔSIR_t	0.030***		−0.091*	−0.07		0.034***	−0.062	−0.048
	(2.78)		(−1.80)	(−1.49)		(3.14)	(−1.39)	(−1.37)
$PosAHF_t$		−0.002	0.000	0.003		0.001	0.002	0.003
		(−0.21)	(−0.05)	(0.44)		(0.05)	(0.21)	(0.54)
$\Delta SIR_t \times PosAHF_t$			0.456**	0.311**			0.357**	0.254**
			(2.44)	(2.08)			(2.13)	(2.02)
Intercept	0.013***	0.015***	0.014***	0.017	0.012***	0.013***	0.012***	0.017
	(3.72)	(4.94)	(4.65)	(1.38)	(3.52)	(4.34)	(4.09)	(1.44)
Controls	No	No	No	Yes	No	No	No	Yes

This table reports results on the return predictability of the monthly change in the short interest ratio (ΔSIR) of industry ETFs on future returns, conditioning on abnormal hedge fund holdings of the ETF's member stock (*PosAHF*). Panel A reports holding period returns of industry ETF portfolios sorted on ΔSIR and *PosAHF*. At each month end, we sort industry ETFs into three groups as in Table 8 based on ΔSIR in that month. Within each ΔSIR portfolio, we further sort industry ETFs into three groups (low, middle, and high) based on *PosAHF* at the latest quarter end. We hold the portfolio in the next month and report the equally weighted portfolio excess return, CAPM alpha, Fama-French three-factor alpha, and Fama-French-Carhart four-factor alpha. Panel B reports the time-series averages of slope coefficients from Fama and MacBeth (1973) cross-sectional regressions of industry ETF returns in the next month (Ret_{t+1}) or percentage *NAV* change in the next month (ΔNAV_{t+1}) on ΔSIR_t, $PosAHF_t$, and their interaction term. ΔNAV_{t+1} is calculated as the monthly change in *NAV* scaled by *NAV* at the previous month end. ΔSIR_t is the change of the short interest ratio in month t. $PosAHF_t$ is defined as the number of member stocks whose abnormal hedge fund holdings is positive in the latest quarter divided by the total number of member stocks at the nearest quarter end prior to month $t+1$. In our control variables, we include stock characteristics as of month t end, including past 12-month returns, log market capitalization, book-to-market ratio, asset growth, operating profitability, gross profitability, investment growth, net issuance, accruals, and net operating assets. The sample period of our analysis is from January 2005 to December 2017, excluding the crisis period (from 2006Q4 to 2008Q4). All standard errors are with Newey-West correction of one lag.t-statistics are reported in the parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

We also run Fama-MacBeth regressions adding *PosAHF* and the interaction term between ΔSIR and *PosAHF* to predict the ETF future return and ΔNAV.

Table 9 reports the results. As shown in panel A (portfolio sorting), when conditioned on high *PosAHF*, the monthly four-factor alpha of the long-short portfolio sorted on ΔSIR increases to 52 bps ($t=2.34$). Conversely, when conditioned on low *PosAHF*, the monthly four-factor alpha becomes negative and insignificant. We find a similar pattern when ETF returns are replaced with ΔNAV. As shown in panel B (Fama-MacBeth regressions), the interaction term of ΔSIR and *PosAHF* positively and significantly predicts both the ETF future return and its ΔNAV. Our results suggest that when hedge funds increase their positions in stocks (e.g., *PosAHF* is high), ΔSIR positively predicts the ETF return, reflecting hedging-motivated short interest in the industry ETF.[23]

6. Conclusion

Can industry ETFs facilitate informed trading and enhance market efficiency? We address this question by examining the *long-the-stock/short-the-ETF* activity prior to earnings announcements. We find that such long-short activity surges before the announcement of positive earnings surprises. More importantly, the relation between long-short activity and earnings surprises is most pronounced among stocks with high industry risk exposure. We further conduct a *diff-in-diff* analysis to study the market efficiency implication and find that after industry ETF inception, member stocks with the strongest PEAD reduction effect are those with the highest industry risk exposure. In addition, we find that the inception of the industry ETF reduces arbitrage risk of its member stocks. These results suggest that the industry ETF can facilitate hedging of industry risk for informed investors with consequent positive effects on market efficiency.

We also study the asset pricing implication of the *long-the-stock/short-the-ETF* activity. We find a positive return predictability of short interest in the industry ETF. Particularly, when the high short interest in the industry ETF coincides with a spike in hedge fund holdings on member stocks, short interest has an even stronger positive predictability for the ETF return. Given that most of the prior studies show the negative return predictability of short interest in the stock, our finding here is novel.

Based on the rich findings in our analysis, we can conclude that the industry ETF has been a positive financial innovation for both investors and the market. Equally intriguing are the broader implications of our research. For example, the economic mechanism unveiled in our study could help some investors,

[23] In Internet Appendix Table A.10, we also find that the measure of long-short activity can significantly and positively predict stock returns and such return predictability is more pronounced among stocks with high industry risk exposure. These results provide additional evidence that the *long-the-stock/short-the-ETF* strategy is used to trade on stocks possessing positive firm-specific information.

particularly less sophisticated investors, realize the hedging benefit of the ETF and expand their investment opportunities. Moreover, following a similar rationale in our study, various ETFs, such as emerging market/commodity ETFs, could help market participants (e.g., hedge funds) hedge a wider range of risk and thus improve market efficiency. Our results here may be particularly useful for designing ETFs to effectively provide this hedging benefit. We believe this is a fruitful area for future research.

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