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ETFs and Information Acquisition

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Abstract

I examine how exchange-traded funds (ETFs) affect incentives to produce information about individual securities. Due to their low trading costs, ETFs can be used to trade on information about less liquid and more constrained stocks that have large weights in the ETF. Using introductions of options on sector ETFs as events that reduce costs of trading on private information, I find that small stocks with large ETF-weight experience an increase in price informativeness compared to similar low ETF-weight stocks. In contrast, I do not find such an effect for large stocks. I conclude that by providing a cheaper way to trade on stock-specific information, ETFs facilitate information acquisition about large ETF-weight stocks, leading to more informative prices.

Keywords – ETF, price informativeness, information acquisition

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1 Introduction

One of the recent developments in financial markets is the rapid growth of exchange-traded funds (ETFs). The increasing size and trading volume raise concerns about the impact of this innovation on price informativeness. One of the concerns is based on the view that ETFs make markets more passive. By free riding on price discovery by active investors and attracting liquidity traders away from the underlying securities, ETFs make it more costly for informed investors to trade on their information. At the same time, even though ETFs have properties of instruments for passive investing, investors can use them to form active portfolios. In this thesis, I argue that because informed investors can use ETFs to trade on their private information about individual stocks, investors are more incentivized to collect fundamental information, leading to more informative prices.

Providing price discovery is one of the main roles of financial markets. By aggregating dispersed information, prices give useful signals for real decisions and efficient allocation of capital (Hayek, 1945; Subrahmanyam and Titman, 1999; Bond et al., 2012). Thus, it is important to understand how ETFs affect the acquisition of new information and the information content of prices.

The idea that ETFs can be used to trade on firm-specific information is based on theoretical and empirical evidence of Subrahmanyam (1991) and Ernst (2020). They show that informed investors use basket securities to trade on their firm-specific information about stocks that are heavily weighted in the basket. By accessing ETF liquidity, informed investors can thus reduce their trading costs. As a result, because rewards to acquiring information increase, investors are willing to spend more effort on collecting information about large ETF-weight stocks.

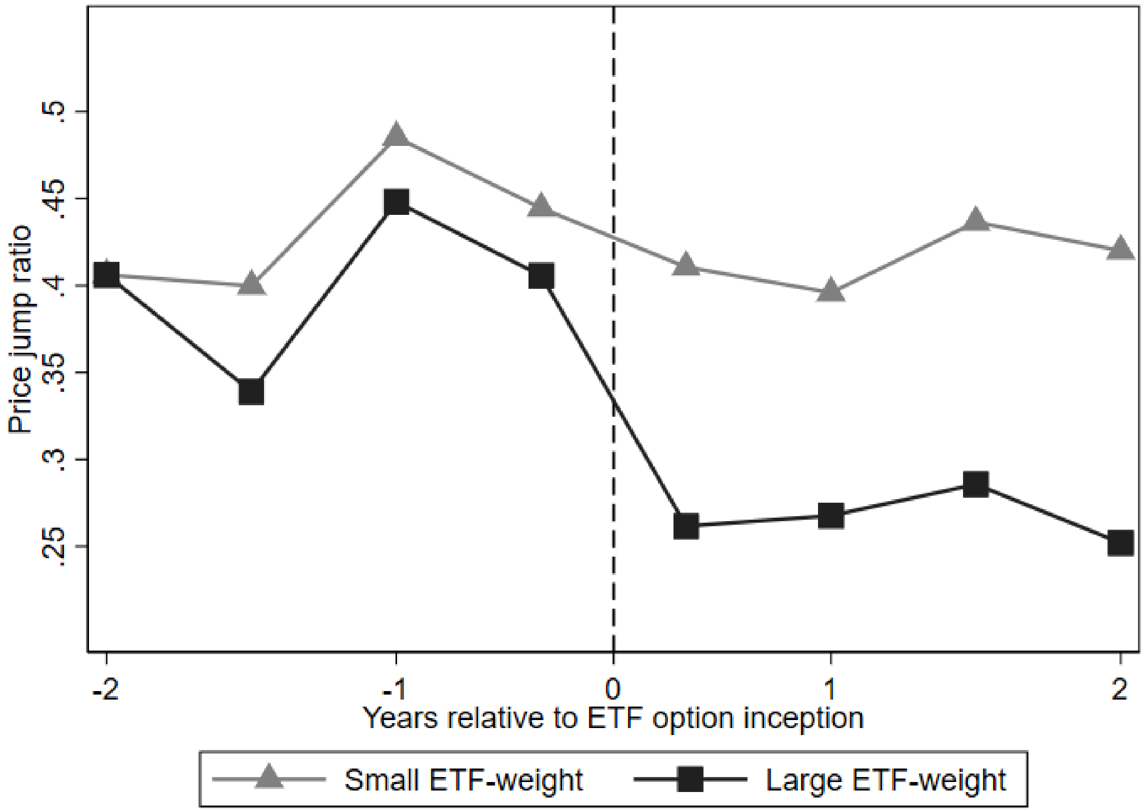
For example, SPDR S&P Retail ETF (XRT) and SPDR S&P Biotech ETF (XBI) are consistently among the most shorted ETFs (Balchunas, 2016). These ETFs are so shorted because they are fairly concentrated and equally weighted, so even small capitalization stocks have large enough weights and are correlated with the ETF. As a result, investors can use these ETFs to get a cheaper (short) exposure to individual stocks that are otherwise difficult to borrow. Such reduction in trading costs should lead to more informed trading and more informative prices.

The difficulty in assessing the impact of ETF ownership on price informativeness lies in that firms with higher ETF ownership are more likely to be larger, have higher institutional ownership, and thus, more informative prices. To address this issue, I use difference-in-difference analysis and examine how price informativeness changes for different groups of stocks around first listings of options on ETFs. By allowing hedging, reducing short sale constraints, and providing higher leverage, stock options facilitate informed trading (Black, 1975; Figlewski and Webb, 1993; Johnson and So, 2012; Hu, 2018). ETF options have very large daily volumes, exceeding those of all stock options (Ramaswamy, 2011). Moreover, ETF options improve liquidity of the underlying ETF (Hu, 2018; Khomyn, 2020). Thus, if the reduction in trading and arbitrage costs that comes from an introduction of options on ETFs encourages investors to collect more information about large ETF-weight stocks, more constrained stocks with large weight in the ETF should experience an increase in price informativeness compared to similar low ETF-weight stocks.

This is exactly what I observe. I focus on sector ETFs as they generally have more concentrated holdings. Using a sample of ETFs that introduced options during 2007-2020, I find that among small stocks, those with ETF-weight above 3% experience a greater increase in price informativeness than stocks with lower weight after options on the ETF are introduced. To measure price informativeness, I use Weller (2018)'s price jump ratio that measures how much information enters prices during the earnings announcement period relative to the total earnings information. Large price jumps during earnings announcements indicate that little information has been acquired in the pre-announcement period, and thus, that the prices are less informative. After the introduction of options on ETFs, large ETF-weight stocks experience an increase in the amount of earnings information acquired in the pre-announcement period compared to small ETF-weight stocks.

Figure 1.1 shows the difference in price jump ratio between small heavy weight and small low weight stocks across time relative to the start of the estimation window (two years before ETF option inception). Before the inception, the price jump ratio of both groups moves similarly. However, after ETF options are introduced, large ETF-weight stocks experience a decrease in price jump ratio (increase in price informativeness) relative to the small ETF-weight stocks. I do not find a similar effect among large market capitalization stocks, which are less likely to benefit from the reduction of arbitrage constraints through an ETF as they are already rather liquid. Since the increase in price informativeness is larger for heavy weight stocks, it is likely at least partially due to investors using ETFs and their derivatives to trade on information about large ETF-weight stocks.

Figure 1.1: Differences in inverse price informativeness measure across time for small stocks



This figure plots the dynamic effects of the introduction of ETF options on the preemption of earnings news for different groups of stocks. I consider a four-year window around the option inception date. The plotted effects come from the predicted point estimates of a difference-in-difference regression with a series of dummy variables for each of the half-year periods, excluding the $[-2\ years, -1.5\ years]$ period, which serves as the baseline (see Table 4.2 for the details of the regression specification). The sample excludes stocks in the top decile of market capitalization. Small ETF-weight stocks are stocks with weight in the ETF below 3%; large ETF-weight stocks — those with the weight above 3%. Price jump ratio is the ratio of earnings information incorporated on the announcement day relative to the total earnings information: $CAR^{T-1,T+2}/CAR^{T-21,T+2}$ (see Table 4.1 for details).

The thesis makes several contributions to the literature. First, it adds to the literature on financial innovation. In the presence of market frictions, an introduction of a seemingly redundant security can alter the flow of information and prices of the underlying securities (Back, 1993). It can attract liquidity traders away from the underlying securities (Subrahmanyam, 1991; Israeli et al., 2017; Cong and Xu, 2016) or increase informed trading due to reductions in trading costs, short sale constraints, and better hedging opportunities (Cao, 1999; Huang et al., 2020; Lundholm, 2021). In this thesis, I show that ETFs, by reducing arbitrage constraints, facilitate more information acquisition about stocks with large ETF-weight.

Second, it joins the growing literature on how ETFs affect the behavior of market participants. Easley et al. (2020) highlight the role of ETFs in creating active portfolios. Huang et al. (2020) find that hedge funds use ETFs to hedge industry risk and trade more aggressively on their firm-specific information. Li and Zhu (2018) show that arbitrageurs use ETFs to create synthetic short positions to circumvent short sale constraints, while Glosten et al. (2020) and Bhojraj et al. (2020) document the role of ETFs in transmitting systematic and industry information. Ernst (2020) demonstrates that investors trade both the stock and the ETF on stock-specific information of large ETF-weight stocks. My results support the view that even though ETFs have the properties of passive investments when viewed as standalone instruments, they facilitate information acquisition and contribute to price discovery.

Third, more broadly, the thesis relates to the empirical literature on the effects of ETFs on financial markets (Ben-David et al., 2018; Da and Shive, 2018; Dannhauser, 2017; Israeli et al., 2017; Hamm, 2014). Glosten et al. (2020) find that ETF activity improves the efficiency of incorporation of systematic information for small stocks, while Bhojraj et al. (2020) show that sector ETF ownership is associated with more efficient transfer of systematic and idiosyncratic information. While I do not study the effect of ETFs on the efficiency of incorporation of information, I also rely on ETFs being a vehicle for less costly informed trading in more difficult-to-reach segments of the market. I show that by reducing trading costs on private information (through an introduction of options on sector ETFs), ETFs improve price informativeness of the underlying large ETF-weight stocks. Similar to Glosten et al. (2020), I find positive effect among small firms.

2 Related literature and hypothesis development

2.1 ETFs literature

A number of recent studies examine how ETFs affect the underlying securities. Some argue that ETFs may distort markets by increasing volatility (Ben-David et al., 2018; Krause et al., 2014), transmitting nonfundamental shocks and creating herding behavior in hard-to-access markets (Bhattacharya and O'Hara, 2018), contributing to excessive return co-movement (Da and Shive, 2018), reducing liquidity of the underlying securities (Israeli et al., 2017; Hamm, 2014). Others find positive effects, such as the reduction in post-earnings-announcement drift (Glosten et al., 2020; Huang et al., 2020), higher liquidity (Saglam et al., 2019), timely incorporation of systematic information (Bhojraj et al., 2020; Glosten et al., 2020).

An important avenue of research is how ETFs affect the price discovery process. The idea that prices serve as a tool to aggregate dispersed information goes back to Hayek (1945). Numerous studies argue that market prices provide useful signals for real decisions (Subrahmanyam and Titman, 1999; Foucault and Gehrig, 2008; Bond et al., 2012). Informative prices help efficient allocation of capital; they reduce information asymmetry about the value of firms' assets and encourage outside investments (Myers and Majluf, 1984). Thus, it is important to study how ETFs affect the acquisition and aggregation of new information about the underlying firms for more efficient capital allocation and better investment decisions.

2.2 Price informativeness

The two main components of the price discovery process are the acquisition of new information and incorporation of the acquired information into prices. Brunnermeier (2005) relates these processes to concepts of "price informativeness" and "informational efficiency". Informational efficiency refers to how much of the *acquired* information is incorporated into prices, while price informativeness is concerned with information acquisition and how much of the *total* information is reflected.

While both concepts relate to the information content of prices, they are concerned with different parts of the price discovery process. Prices can be efficient in incorporating current information set, but how informative these prices depends on how rich the information set is. An increase in the amount and quality of acquired information makes prices more informative; however, at the same time, prices may become less efficient at incorporating this new, richer information set, and vice versa. When prices reflect all acquired information, they follow a random walk process, and the returns cannot be predicted from observing past prices. However, these prices might not reflect the value of fundamentals, and thus, might not be informative. Since real decisions rely on correct valuations, price informativeness is an important part of the price discovery process.

2.2.1 Do ETFs encourage information acquisition?

There is no consensus in the literature about how ETFs affect stock price informativeness. Grossman and Stiglitz (1980) model suggests that as rewards to acquiring information increase, more information is collected. In this setting, informed (active) investors acquire costly information and trade with uninformed investors to profit on the informational advantage. This trading reveals information of the informed investors and incorporates it into prices. If the costs of collecting the information or trading on the information decrease, informed investors receive larger profits, leading to more information gathering, and vice versa.

In the context of active and passive investing, Garleanu and Pedersen (2019) show that the number of active managers increases as the cost of information falls. However, as fees for passive investment decrease, active investing becomes relatively more expensive, so more funds are allocated to passive investments and less to active. Thus, as the share of passive ownership increases, less information is produced and enters prices.

In the same vein, Sammon (2021), viewing ETFs as one of the instruments for passive investing, shows that passive ownership decreases price informativeness by increasing the share of uninformed investors and decreasing attention to firm-specific risks. Israeli et al. (2017) show that ETF ownership limits the number of shares available for trading in the underlying market and decreases the number of liquidity traders as they move to trading ETFs, where the losses from trading with informed investors are lower. As a result, transaction costs of the underlying securities increase, reducing profits of informed investors and leading to less informative prices.

On the other hand, ETFs are not necessarily passive investment instruments. Many ETFs are used as building blocks of active portfolios, making it less costly for investors to trade on their superior information. Easley et al. (2020) show that most ETFs are rather active, either in form (seek to generate alpha) or in function (used in building active portfolios). Even if an ETF has characteristics of a passive instrument when viewed as a standalone security, it contributes to investors' portfolios by creating exposures that help generate abnormal returns. Therefore, while broad market ETFs are closer to passive instruments, more specialized ETFs can be used more actively.

When used in more complex trading strategies, ETFs can reduce arbitrage constraints and trading costs, increasing profits from informed trading and stimulating information acquisition. In a theoretical paper, Bhattacharya and O'Hara (2018) show that ETFs allow access to hard-to-access or illiquid assets and that for these assets, informed trading takes place in the ETFs. They show that as a result, ETF order flow brings in more information, making prices more informative; however, individually, hard-to-access assets may suffer from persistent non-fundamental shocks and less informative prices.

Some studies argue that composite securities facilitate the incorporation of systematic information but may harm the acquisition of firm-specific information. Cong and Xu (2016) model introduction of a composite security and show that it encourages factor investing. However, by draining away factor liquidity traders from the underlying market, ETFs decrease liquidity of the underlying securities and make it less profitable for asset-specific informed traders to exploit their advantage. The authors argue that for less liquid assets, the increase in the systematic component of prices brought by the introduction of a composite security dominates the decrease in the firm-specific component, making prices more informative. Similarly, Glosten et al. (2020) find that ETFs accelerate the incorporation of systematic earnings information for small firms and stocks with low analyst following — stocks for which without ETFs, it is relatively harder to trade on systematic information.

Other studies argue that ETFs can facilitate trading on firm-specific information. Li and

Zhu (2018) demonstrate that ETFs reduce short-sale constraints through share lending channel and through “synthetic shorting”. Synthetic shorting — shorting an ETF and getting a long position in other stocks — gives the same negative exposure as shorting an individual stock, which is often constrained. It has long been argued that short-sale constraints reduce the amount of negative opinion reflected in prices (Miller, 1977). By alleviating this arbitrage constraint, ETFs encourage investors to target overpriced securities, improving price informativeness. The authors also show that ETF ownership reduces various pricing anomalies induced by short-sale constraints.

Another feature of ETFs that increases the value of being informed about firm-specific information is that ETFs provide an effective way of hedging systematic information. Lundholm (2021) models the introduction of an ETF and finds that prices become more informative because ETF hedging allows risk-averse firm-specific traders to take more aggressive positions on their private information. Empirically, Huang et al. (2020) show that hedge funds use industry ETFs (IETFs) to hedge industry risks when trading on firm-specific information and that they trade more aggressively when ETF hedging is available. They also find that after the introduction of IETFs, post-earnings-announcement drift is reduced more for stocks with high industry exposure, suggesting that the hedging mechanism of IETFs improves market efficiency.

ETFs are very liquid, generally more liquid than the underlying stocks (Ben-David et al., 2018). They have larger trading volumes, narrower bid-ask spreads, and allow for faster exit from short positions (Li and Zhu, 2018). Given these advantages, investors can use ETFs to get cheaper exposure to more difficult-to-trade assets. Ernst (2020) models and shows that investors with stock-specific information use an ETF in tandem with the stock to trade on their single-stock information when the stock has a sufficiently large weight in the ETF or is sufficiently volatile. The idea is that an investor with an informational advantage on a stock that comprises a large part of an ETF also has an informational advantage on the whole ETF. By accessing ETF liquidity, firm-specific informed traders increase their rewards from trading on the information and are more incentivized to produce the information. Similarly, Subrahmanyam (1991) models that after a basket security is introduced, more investors become informed about stocks that have large weights in the basket. In contrast, for small weight securities, firm-specific price informativeness decreases due to lower liquidity in the underlying market as more uninformed traders migrate to the basket security.

Overall, the evidence and theory predictions about how ETFs affect the acquisition of information on individual firms are mixed. Some ETFs, such as broad ETFs that just hold a market portfolio, are very close to pure passive instruments and are unlikely to facilitate information collection. Others, for example, sector ETFs, are more likely to be used for informed trading. By reducing trading costs and arbitrage constraints, they may encourage the acquisition of information for some assets.

2.3 Hypothesis development

Previous literature suggests various channels through which ETF ownership can either harm or improve price informativeness. In this thesis, I focus on one of them — that informed traders can use ETF liquidity to trade on their firm-specific information.

Sector ETFs are popular among investors, being among the most traded ETFs (Bhojraj et al., 2020). They are usually more concentrated and more correlated with the constituent stocks. Thus, if a stock has a large weight in a sector ETF, investors can use the ETF to trade on their stock-specific information. Without an ETF, some assets are hard to reach or costly to trade or short. With an ETF, investors can reduce their trading costs by accessing ETF liquidity. For less liquid and more constrained stocks, getting a (noisy) exposure to the stock through a more liquid ETF can motivate investors to gather more stock information.

To see whether the reduction of trading costs and arbitrage constraints by ETFs encourages investors to acquire more information and improves price informativeness, I focus on the introduction of options on sector ETFs. Option contracts can be expensive or unavailable for some stocks, while ETF options generally have very high daily volumes (Ramaswamy, 2011). The literature highlights the benefits of options, such as hedging, relaxing short-sale and leverage constraints, and that these benefits facilitate informed trading (Black, 1975; Figlewski and Webb, 1993; Johnson and So, 2012; Hu, 2018). Moreover, option listings improve liquidity of the underlying assets (Hu, 2018). ETF options improve liquidity of ETFs by reducing costs of hedging market makers' inventory portfolios and increasing uninformed trading and arbitrage trading between the derivatives market and the ETF

(Hu, 2018; Khomyn, 2020).

Therefore, if informed investors use ETFs to trade on large ETF-weight stock's information, the introduction of options on ETFs should reduce the trading costs because of increased ETF liquidity and the availability of option contracts. By increasing rewards to acquiring information, the introduction of options on ETFs should thus lead to more effort spent on collecting information on large ETF-weight stocks, resulting in more informative prices, especially for less liquid and more constrained stocks.

On the other hand, if investors mainly use sector ETFs as passive investments or as vehicles to trade on factor information, more liquid ETFs and the availability of derivatives will attract even more uninformed traders and factor traders away from the underlying securities. In this case, the introduction of options on ETFs makes it more costly for firm-specific informed investors to trade on their private information, leading to less information gathering and less informative prices.

3 Data

3.1 ETF-level data

I collect option listing data from several sources. I use Option Clearing Corporation (OCC) for listings between 2013 and 2021 and Chicago Board Options Exchange (CBOE) for listings starting from 2007, identified as the first day the ETF option is traded at CBOE exchanges. Earlier listing dates are collected individually for each ETF, but none of those ETFs enter the final sample.

Following previous studies, I identify ETFs as securities on Center for Research in Security Prices (CRSP) with share code 73. To get ETF names, I merge the list from CRSP with the list of all equity ETFs from ETF.com using securities' tickers. I focus on sector ETFs that hold U.S. equities; thus, I remove inverse and leveraged ETFs. I identify sector ETFs by their names, as the name usually includes the industry, and confirm with the segment from ETF.com. Further, I remove ETFs in which only large-cap stocks have a weight above 1%, as it is less likely that investors would use ETFs to get exposure to these stocks because they are already very liquid. To alleviate concerns that ETF inceptions interfere with option listing effects, I remove ETFs that have their first ETF option listed during 1.5 years since ETF inception. The final sample consists of 45 ETFs that introduced their first options from 2007 to 2020.

ETFs are required to disclose their holdings quarterly. Thus, for each of the ETFs, I collect its holdings from SEC N-CSR and N-Q reports for the closest quarter before ETF option inception. I then combine the holdings information with the firm-level data. On average, the sample ETF consists of 47 firms. These ETFs are fairly concentrated: the average ETF-weight of a stock is 2%.

3.2 Firm-level data

The price informativeness measure requires information around earnings announcements. I collect quarterly earnings announcement dates and book value of equity from Compustat. I exclude earnings announcements that are less than 45 days from the previous earnings announcement. Daily stock returns, prices, and the number of shares outstanding are collected from CRSP. The sample includes common stocks (CRSP share codes 10 and 11) that are listed on NYSE, AMEX, or NASDAQ. I collect daily option volume data from CBOE and the risk factors and risk-free rates from Kenneth French's website.

3.3 Construction of key variables

3.3.1 Price informativeness measure

Price informativeness is concerned with how much information is produced in the economy about the value of fundamentals. The difficulty in measuring price informativeness lies in that the set of total acquirable information about a firm is not observable. One of the ways to address this issue is to use a price informativeness measure around earnings announcements. Public disclosure reveals total information, so it shows how much information was potentially acquirable in the pre-announcement period. The acquired information does not always enter the market. However, after the information becomes public, its value decreases, so informed investors want to trade on their private information until prices reach their estimated post-announcement values, revealing all their acquired information.

Using this logic, Weller (2018), adopting Meulbroek (1992)'s measure, proposes the price jump ratio ($Jump_{it}$) that calculates the fraction of the total earnings information incorporated on the announcement day:

$$Jump_{it} = \frac{CAR_{it}^{(T-1,T+b)}}{CAR_{it}^{(T-a,T+b)}}, \tag{3.1}$$

where $CAR_{it}^{(T-a,T+b)}$ is the cumulative abnormal return of stock i from a days before the earnings announcement (to capture pre-announcement run up) to b days after the announcement (to capture post-announcement drift).

The idea is that if investors discover more information during the pre-announcement period, public disclosure generates less news, leading to a smaller reaction. Thus, lower values of the price jump ratio indicate that prices are closer to their post-announcement values and are more informative.

Following Weller (2018), I first estimate daily abnormal returns relative to Fama and

French (1992) three-factor model. The model is estimated using daily returns over the 365 day period ending 90 days before the earnings announcement. I require that there are at least 63 observations during the estimation window. Thus, the cumulative abnormal return for company i on date t during $[T_1, T_2]$ window is estimated by:

$$CAR_{it}^{T_1,T_2} = \sum_{t=T_1}^{T_2} (r_{it} - \alpha_i - \beta_{im} r_{mt} - \beta_{is} SMB_t - \beta_{ih} HML_t). \tag{3.2}$$

The price jump ratio, $Jump_{it}$, is the ratio of cumulative abnormal return during the announcement window relative to cumulative abnormal return before and including the earnings announcement. I define the announcement window as $[-1, 2]$ days around the earnings announcement and the pre-announcement window as $[-21, 2]$ days relative to the earnings announcement.

Similarly to Weller (2018), I require the total announcement period returns to be relatively large to represent non-zero earnings announcement information events. Therefore, I exclude events in the lowest quartile of absolute $CAR[-21, 2]_{it}$. This exclusion reduces the noise created by near-zero denominators from events that do not bring informational distortions to the market.

3.3.2 Control variables

In the analysis, I use a set of control variables that are associated with price informativeness: market capitalization ($Size$), book-to-market ratio (BM), and idiosyncratic volatility ($IVOL$). Market capitalization is measured as the average market capitalization over the month ending 30 calendar days before the earnings announcement. I use the log of market capitalization as an independent variable. Following Fama and French (1992), I exclude observations with negative values of book-to-market ratios and winsorize the ratio at the 0.5% and 99.5%. I use idiosyncratic volatility as the measure of firm-specific risk. I calculate it as the variance of residual values from fitting Fama and French (1992) three-factor model using daily stock returns over the previous year. I require at least 200 observations for the estimation of the model.

The average (median) price jump ratio for the sample starting two years before and ending two years after the ETF option introduction is 0.4 (0.38). The average (median) market capitalization is 16.4 billion (3.86 billion), suggesting that the sample ETFs consist of generally large firms.

4 Research design and empirical analysis

4.1 Main results

To test whether the possibility of trading ETFs on information about large ETF-weight stocks encourages investors to acquire more information, I use difference-in-difference analysis. I compare price informativeness of stocks with large weight in the ETFs to stocks with low ETF-weight, before and after the introduction of ETF options. Following Huang et al. (2020), I consider an ETF and one of its stocks as a pair. Panel A of Table 4.1 reports summary statistics for ETF-stock pairs with ETF-weight above 3% and below 3% in the two-year period before ETF option inception. On average, large ETF-weight stocks have much larger market capitalization, lower book-to-market ratio, and lower idiosyncratic volatility. They are more likely to have higher institutional ownership and better information environments, and thus, more informative prices.

My hypothesis is that more constrained stocks experience an increase in the amount of earnings information incorporated into prices in the pre-announcement period following ETF option introduction. Thus, to capture the effect and make treatment and control groups more similar, I focus on smaller stocks. Each quarter I divide all stocks in the market into deciles based on their average market capitalization over the previous month. I exclude stocks in the top decile as they are less likely to benefit from utilizing ETF liquidity. The remaining stocks are assigned to the treatment group if their ETF-weight is above 3% and to the control group if the weight is below 3%.

Panel B of Table 4.1 reports summary statistics for treatment and control ETF-stock pairs in the two-year period before the introduction of ETF options. Generally, both groups have similar characteristics. As expected, because treatment firms have larger weights in the ETFs, they, on average, have larger market capitalization (3.8 billion for the treatment group vs. 2.6 billion for the control group). Despite these differences, if the price informativeness measure of both groups follows a similar trend before ETF option introduction, the differences between the groups in the post-event period can be used to make a causal interpretation. Later in this section, I provide evidence that the parallel trend assumption holds.

Table 4.1: Summary statistics in the pre-treatment period

Panels A and B report summary statistics on the quarterly observations for ETF-stock pairs in the two-year period prior to the introduction of ETF options. Panel A divides the sample into ETF-stock pairs with ETF-weight above 3% and below 3%. For Panel B, each quarter, all stocks are divided into deciles based on their average market capitalization over the previous month. Stocks in the top deciles are excluded from the sample. ETF-stock pairs are assigned to the treatment group if their ETF-weight is above 3% and to the control group if the weight is below 3%. $Jump$ is the price jump ratio of Weller (2018), estimated as $CAR^{T-1,T+2}/CAR^{T-21,T+2}$, where $CAR^{T-a,T+b}$ is the cumulative abnormal return from a days prior to the earnings announcement to b days after the announcement relative to returns from Fama and French (1992) three-factor model. $Size$ is the average market capitalization (in $billion) over the previous month, ending 30 calendar days before the earnings announcement. BM is book-to-market ratio, excluding negative observation and winsorized at 0.5% and 99.5%. $IVOL$ is idiosyncratic volatility, measured as the variance of residuals from fitting Fama and French (1992) three-factor model using daily stock returns over the previous year. The difference compares the mean values between the groups. The sample covers ETF option inceptions during 2007-2020. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

Panel A: Summary statistics in the pre-treatment period for the whole sample

	ETF-weight $\geq$ 3%			ETF-weight < 3%			Difference	
	Mean	SD	No. Obs.	Mean	SD	No. Obs.	Diff	t-Statistic
$Jump$	0.37	0.57	2367	0.41	0.65	8994	0.04***	(3.0)
$Size$	28.23	51.56	3259	12.55	44.15	12798	-15.68***	(-17.5)
BM	0.43	0.40	3184	0.51	0.40	12462	0.08***	(10.1)
$IVOL$	3.85	6.39	3235	4.28	7.39	12587	0.43***	(3.0)

Panel B: Summary statistics in the pre-treatment period for the treatment sample

	Treatment			Control			Difference	
	Mean	SD	No. Obs.	Mean	SD	No. Obs.	Diff	t-Statistic
$Jump$	0.46	0.65	965	0.42	0.68	6973	-0.04*	(-1.7)
$Size$	3.78	2.46	1269	2.56	2.15	9621	-1.22***	(-18.7)
BM	0.52	0.56	1236	0.53	0.43	9370	0.01	(0.8)
$IVOL$	5.46	7.86	1259	5.00	8.28	9442	-0.46*	(-1.9)

I test the hypothesis using difference-in-difference analysis in the $[-2\ years, +2\ years]$ window around ETF option inception. For each ETF-stock pair I define a variable $Post$ that takes a value of zero for the two-year period prior to ETF option inception and one for the two-year period after the inception. $Treat$ is a variable that equals one for ETF-stock pairs in the treatment group and zero for the control group. To estimate the effect of the introduction of ETF options on price informativeness, I run the following regression:

$$Jump_{it} = \alpha + \beta_1 Treat_i \times Post_{it} + \beta_2 Post_{it} + \beta_3 Treat_i + \beta_4 X_{it} + \theta_i + \theta_t + \varepsilon_{it}, \quad (4.1)$$

where X_{it} is a vector of control variables that are associated with price informativeness: log of market capitalization ($ln(Size)$), book-to-market ratio (BM), and idiosyncratic volatility ($IVOL$). I control for ETF-stock fixed effects (θ_i) and year-quarter fixed effects (θ_t). The standard errors are clustered by ETF-stock.

Table 4.2: Impact of the introduction of ETF options on the preemption of earnings news

This table reports the difference-in-difference analysis on the impact of ETF option inception on the preemption of earnings news. Each quarter, all stocks are divided into deciles based on their average market capitalization over the previous month. Stocks in the top deciles are excluded from the sample. ETF-stock pairs are assigned to the treatment group if their ETF-weight is above 3% and to the control group if the weight is below 3%. I then examine the impact of ETF option inception on price informativeness in the $[-2\ years, +2\ years]$ window around the option inception date using the following regression:

$$Jump_{it} = \alpha + \beta_1 Treat_i \times Post_{it} + \beta_2 Post_{it} + \beta_3 Treat_i + \beta_4 X_{it} + \theta_i + \theta_t + \varepsilon_{it},$$

the dependent variable, $Jump$, is the price jump ratio, as defined in Table 4.1. $Post$ is a dummy that equals one for the post-inception period and zero for the pre-inception period. $Treat$ is a dummy variable that equals one for the treatment group and zero for the control group. Control variables include log of market capitalization, book-to-market ratio, and idiosyncratic volatility, which are defined in Table 4.1. I control for both ETF-stock and year-quarter fixed effects. The sample covers ETF option inceptions during 2007-2020. The standard errors are clustered by ETF-stock. t statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

Dependent variable:	$Jump$	
	(1)	(2)
$Post \times Treat$	-0.105***	-0.0935**
	(-2.67)	(-2.33)
$Post$	-0.0416	-0.0470*
	(-1.54)	(-1.72)
$ln(Size)$		-0.0456*
		(-1.70)
BM		-0.0480
		(-1.11)
$IVOL$		-0.00135
		(-0.82)
Year-quarter FE	Yes	Yes
ETF-firm FE	Yes	Yes
Adj. R^2	0.0162	0.0175
Observations	15022	14559

The coefficient of interest is β_1, the coefficient on the interaction term $Post \times Treat$. It captures how price jump ratio changes for the treatment firms relative to the control firms after the introduction of ETF options. If informed traders use ETFs to trade on the information about large ETF-weight stocks, the treatment group should experience a greater increase in price informativeness compared to the control group. Thus, I expect that more information is acquired during the pre-announcement period about the upcoming news of the treatment firms, leading to a lower price jump ratio. Hence, I expect β_1 coefficient to be negative.

Table 4.2 reports the results of the above regression. Consistent with the hypothesis, β_1 is negative. The effect is both statistically and economically significant. After ETF option introduction, the price jump ratio decreases by 0.09 for the treatment group relative to the control group. Before the event, the median price jump ratio for the treatment stocks is 0.4, indicating that around 40% of information is revealed during earnings announcements. A decrease of price jump ratio by 0.09 for a median firm represents a 22.5% increase in the amount of acquirable private information that enters the price in the pre-announcement period.

The main assumption in the difference-in-difference analysis is the parallel trend assumption — that in the absence of treatment, the treatment and control groups follow similar trends. Thus, to validate the assumption, I estimate treatment effects at different time periods using the following regression:

$$\begin{aligned} Jump_{it} = \alpha + \sum_{k \in \{-2,-1,+1,+2\}} \beta_{1,k} Treat_i \times Yr(k)_{it} + \sum_{k \in \{-2,-1,+1,+2\}} \beta_2 Yr(k)_{it} + \\ \beta_3 Treat_i + \beta_4 X_{it} + \theta_i + \theta_t + \varepsilon_{it}, \end{aligned} \tag{4.2}$$

where $Yr(k)$ is a dummy variable indicating year-periods relative to ETF option inceptions. Control variables are the same as in the regression 4.1, and I further require that all firms have observations for eight quarters before and after option inception dates. $Yr(-2)$ (indicating $[-2\ years, -1\ year]$ window) is omitted from the regression and serves as the baseline. Table 4.3 presents the results. The coefficient on the interaction term $Yr(-1) \times Treat$ measures how price jump ratio changes for the treatment group relative to the control group during $[-1\ year, 0]$ period compared to the base period. The coefficient is both statistically and economically insignificant, providing evidence that the parallel trend assumption holds. Moreover, after the introduction of ETF options, treatment stocks experience a decrease in price jump ratio relative to the control group. This evidence provides support for the parallel trend assumption and suggests that the observed results are not driven by the continuation of pre-option introduction trends.

Table 4.3: Dynamic effects of the introduction of ETF options on the preemption of earnings news

The table reports the dynamic effects of ETF option inception on the preemption of earnings news. I use the sample from Table 4.2 and further require that all firms have observations for eight quarters before and after option inception dates. I estimate the effects using a modified difference-in-difference regression from Table 4.2, in which I replace the *Post* dummy with a series of dummy variables $Yr(k)$, where k takes values of (-2, -1, 1, 2) to indicate year-periods relative to ETF option inception. $Yr(-2)$ (indicating $[-2\ years, -1\ year]$ window) is omitted and serves as the baseline. I run the following regression:

$$Jump_{it} = \alpha + \sum_{k\in\{-2,-1,+1,+2\}} \beta_{1,k} Treat_i \times Yr(k)_{it} + \sum_{k\in\{-2,-1,+1,+2\}} \beta_2 Yr(k)_{it} + \beta_3 Treat_i + \beta_4 X_{it} + \theta_i + \theta_t + \varepsilon_{it},$$

the dependent variable, *Jump*, is the price jump ratio, as defined in Table 4.1. *Treat* is a dummy variable that equals one for the treatment group and zero for the control group. Control variables include log of market capitalization, book-to-market ratio, and idiosyncratic volatility. I control for both ETF-stock and year-quarter fixed effects. Standard errors are clustered at ETF-stock level. t statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

Dependent variable:	*Jump*	
	(1)	(2)
$Yr(-1) \times Treat$	-0.0186	-0.00839
	(-0.37)	(-0.17)
$Yr(+1) \times Treat$	-0.116**	-0.109*
	(-2.02)	(-1.90)
$Yr(+2) \times Treat$	-0.153**	-0.129**
	(-2.48)	(-2.11)
$Yr(-1)$	0.101***	0.0969***
	(2.86)	(2.67)
$Yr(+1)$	0.0820	0.0715
	(1.37)	(1.17)
$Yr(+2)$	0.142	0.132
	(1.59)	(1.44)
Controls	No	Yes
Year-quarter FE	Yes	Yes
ETF-firm FE	Yes	Yes
Adj. R^2	0.0188	0.0196
Observations	11670	11392

To provide further evidence that the introduction of ETF options reduces price jump ratio for the treatment group, I use a series of placebo tests in which I move ETF option inception dates two years back, three years back, and two years forward. Table 4.4 presents the results. In all the tests, the coefficients on the interaction term $Post \times Treat$ are statistically insignificant.

Table 4.4: ETF option inception impacts on the preemption of earnings news: placebo dates

This table repeats the difference-in-difference analysis on the impact of ETF option inception on the preemption of earnings news from Table 4.2 using pseudo-event dates. For each of the three regressions, I move the ETF option inception date two years back, three years back, and two years forward respectively. The dependent variable, *Jump*, is the price jump ratio, as defined in Table 4.1. *Post* is a dummy that equals one for the two-year period after the pseudo-event date and zero for the two-year period before the pseudo-event date. Treatment groups are defined in Table 4.2. Control variables include log of market capitalization, book-to-market ratio, and idiosyncratic volatility, which are defined in Table 4.1. I control for both ETF-stock and year-quarter fixed effects. The standard errors are clustered by ETF-stock. t statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

	−2 years	−3 years	+2 years
Dependent variable:		*Jump*	
$Post \times Treat$	0.00634	0.0119	0.0130
	(0.19)	(0.39)	(0.27)
Post	-0.0357	0.00869	0.0520*
	(-1.50)	(0.34)	(1.93)
Controls	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
ETF-firm FE	Yes	Yes	Yes
Adj. R^2	0.0136	0.0161	0.0233
Observations	14676	14288	12446

Next, I show that there is no such effect among large stocks, since investors can get cheap exposure to these stocks directly as they are generally more liquid and less constrained. Using the sample of the top decile by market capitalization, I assign stocks to the treatment group if they have ETF-weight above 3% and assign the rest to the control group. I run the main specification and find no significant difference in the impact of ETF option inception on price jump ratio between the treatment and control groups. The coefficient on the interaction term is both smaller than in the main analysis and insignificant. Table 4.5 presents the results.

Overall, the results provide evidence that smaller firms with large weight in the ETF benefit from the introduction of ETF options. They indicate that by accessing ETF liquidity and its derivatives to get exposure to an individual stock, investors use ETFs for less costly informed trading. The results collaborate the evidence of Ernst (2020) that investors trade ETFs on information about large ETF-weight stocks and suggest that such trading improves price informativeness.

Table 4.5: Impact of the introduction of ETF options on the preemption of earnings news for large stocks

This table reports the difference-in-difference analysis on the impact of ETF option inception on the preemption of earnings news for large stocks. Each quarter, all stocks are divided into deciles based on their average market capitalization over the previous month. The sample includes stocks in the top decile. ETF-stock pairs are assigned to the treatment group if their ETF-weight is above 3% and to the control group if the weight is below 3%. I then examine the impact of ETF option inception on price informativeness in the $[-2\ years, +2\ years]$ window around the option inception date using the following regression:

$$Jump_{it} = \alpha + \beta_1 Treat_i \times Post_{it} + \beta_2 Post_{it} + \beta_3 Treat_i + \beta_4 X_{it} + \theta_i + \theta_t + \varepsilon_{it},$$

the dependent variable, *Jump*, is the price jump ratio, as defined in Table 4.1. *Post* is a dummy that equals one for the post-inception period and zero for the pre-inception period. *Treat* is a dummy variable that equals one for the treatment group and zero for the control group. Control variables include log of market capitalization, book-to-market ratio, and idiosyncratic volatility, which are defined in Table 4.1. I control for both ETF-stock and year-quarter fixed effects. The sample covers ETF option inceptions during 2007-2020. The standard errors are clustered by ETF-stock. t statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

Dependent variable:	*Jump*	
	(1)	(2)
$Post \times Treat$	-0.0387	-0.0346
	(-1.20)	(-1.05)
$Post$	-0.00841	-0.00199
	(-0.22)	(-0.05)
$ln(Size)$		-0.0224
		(-0.47)
BM		-0.0471
		(-0.76)
$IVOL$		0.00265
		(1.13)
Year-quarter FE	Yes	Yes
ETF-firm FE	Yes	Yes
Adj. R^2	0.0250	0.0257
Observations	6608	6421

ETF options can be used to hedge industry information, suggesting that improvement in price informativeness can come from more aggressive trading on firm-specific information when industry information is hedged, as in Huang et al. (2020). However, because price informativeness increases more for large ETF-weight stocks, it likely comes from investors using ETFs to trade on large ETF-weight firms' information, unless large ETF-weight stocks have higher industry exposure. Huang et al. (2020) do not find significant differences in size between high industry exposure and low industry exposure stocks of industry ETFs. Thus, higher price informativeness of large ETF-weight stocks after the introduction of ETF options can be at least partially attributable to trading ETFs on single stock information.

4.2 Robustness checks and additional analysis

As a robustness test, I use alternative definitions of treatment and control groups. The main hypothesis is that more constrained stocks benefit from the introduction of options on ETFs. Thus, I repeat the main analysis for stocks with large relative spread and low option volume. Average relative spread is measured as the average daily bid-ask spread scaled by midpoint over the previous year, ending 30 days before the earnings announcement. Option volume is measured as the average daily trading volume of listed stock options on CBOE exchanges over the previous year, ending 30 days before the earnings announcement. I assume that stocks with no option volume do not have listed options. Firms with low option volume are more likely to have costly option contracts. Thus, they are more likely to benefit from more liquid ETF options if investors use ETFs and their derivatives to trade on information about individual stocks. The limitation of this variable is that it only covers CBOE exchanges (around 30% of the U.S. option market volume).

Every quarter I sort all stocks into deciles based on their average relative spreads and option volume. In the first set of tests, I exclude stocks in the bottom decile of relative spread (most liquid stocks). In the second, I exclude stocks in the top two deciles of option volume. Afterward, I assign ETF-stock pairs with the ETF-weight above 3% to the treatment group and the rest to the control group and repeat the main analysis (regression 4.1). Table 4.6 presents the main results and Table A1.1 confirms parallel trend assumption. Consistent with the main analysis, among more constrained stocks, those with large ETF-weight experience an increase in price informativeness relative to low-weight stocks after ETF options are introduced.

As another robustness test, I use the same sample as in the main analysis (in which I exclude the top decile of market capitalization) and replace $Treat$ indicator variable with

Table 4.6: Impact of the introduction of ETF options on the preemption of earnings news: alternative treatment groups

This table repeats the difference-in-difference analysis on the impact of ETF option inception on the preemption of earnings news from Table 4.2 using alternative treatment and control groups. Each quarter I sort all stocks into deciles based on their average relative spreads and option volume. First two columns present results from a sample that excludes stocks in the bottom decile of relative spread; the last two columns — from a sample that excludes stocks in the top two deciles of option volume. Average relative spread is measured as the average daily bid-ask spread scaled by midpoint over the previous year, ending 30 days before the earnings announcement. Option volume is measured as the average daily trading volume of listed stock options on CBOE exchanges over the previous year, ending 30 days before the earnings announcement. I assign ETF-stock pairs with the ETF-weight above 3% to the treatment group and the rest to the control group. The variables and the regression specification are the same as in Table 4.2. t statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

Sample:	Relative spread		Option volume	
Dependent variable:		*Jump*		
$Post \times Treat$	-0.0880***	-0.0870**	-0.0929***	-0.0926***
	(-2.62)	(-2.52)	(-2.76)	(-2.72)
$Post$	-0.0361	-0.0389	-0.0453*	-0.0451*
	(-1.39)	(-1.48)	(-1.72)	(-1.69)
$ln(Size)$		-0.0703***		-0.0808***
		(-2.77)		(-2.67)
BM		-0.0655		-0.0263
		(-1.56)		(-0.72)
$IVOL$		-0.00180		-0.00266
		(-1.19)		(-1.31)
Year-quarter FE	Yes	Yes	Yes	Yes
ETF-firm FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0151	0.0174	0.0184	0.0197
Observations	16011	15505	15049	14613

a continuous variable $Weight$ that represents the weight of the stock in the ETF. Table 4.7 presents the results. Consistent with the hypothesis, stocks with larger weight in the ETF experience a larger decrease in price jump ratio after ETF option inception. Having a larger ETF-weight by 1% decreases the price jump ratio by 0.02. I repeat the same test for alternative treatment and control groups and find similar results.

Additionally, in Appendix A2.1, I use different weight cutoffs for the treatment group against the same control group — stocks with ETF-weight below 2%. The results are consistent with the previous analysis: small stocks with larger ETF-weight experience a greater increase in price informativeness.

Table 4.7: Impact of the introduction of ETF options on the preemption of earnings news: continuous variables

This table reports the difference-in-difference analysis on the impact of ETF option inception on the preemption of earnings news. I estimate the model using a modified regression from Table 4.2, in which I replace $Treat$ dummy with a continuous variable $Weight$ that represents the weight of the stock in the ETF. The first column uses the sample from Table 4.2; the second and third columns use the samples from Table 4.6. I estimate the effects in the $[-2\ years, +2\ years]$ window around ETF option inception. The dependent variable, $Jump$, is the price jump ratio, as defined in Table 4.1. $Post$ is a dummy that equals one for the post-inception period and zero for the pre-inception period. Control variables include log of market capitalization, book-to-market ratio, and idiosyncratic volatility, which are defined in Table 4.1. I control for both ETF-stock and year-quarter fixed effects. The sample covers ETF option inceptions during 2007-2020. The standard errors are clustered by ETF-stock. t statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

Sample:	Market capitalization	Relative spread	Option volume
Dependent variable:		$Jump$	
$Post \times Weight$	-1.940*	-2.299**	-2.285**
	(-1.73)	(-2.45)	(-2.57)
$Post$	-0.0289	-0.0219	-0.0140
	(-0.92)	(-0.73)	(-0.47)
Controls	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
ETF-firm FE	Yes	Yes	Yes
Adj. R^2	0.0173	0.0195	0.0174
Observations	14559	14613	15505

5 Conclusion

The rapid growth of ETFs raises concerns that ETFs may make the market more passive and harm price discovery. In this thesis, I examine the role of ETFs in facilitating information acquisition and improving price informativeness. ETFs are generally liquid, have lower shorting costs and actively traded derivatives. Thus, investors with information about stocks with large weight in the ETF can access ETF liquidity and get exposure to the stock through an ETF. The reduction in trading costs should stimulate investors to acquire more information about these stocks.

Consistent with this hypothesis, using difference-in-difference analysis, I find that small firms with large ETF-weight benefit from the introductions of options on ETFs. After ETF options are introduced, more earnings information enters prices in the pre-earnings announcement period for small stocks with large weight in the ETF compared to similar low ETF-weight stocks. I find that a median large ETF-weight firm experiences a 22.5% increase in the amount of information that enters prices early. Moreover, I do not find such an effect among large stocks, which are generally more liquid and less constrained. The results suggest that by reducing trading and arbitrage costs, ETFs improve price informativeness of more constrained stocks with large ETF-weight.

The findings highlight the role of ETFs in reaching different segments of the market. Informed traders can use ETFs to trade on information about less liquid stocks, resulting in investors spending more effort on collecting information on these stocks. Thus, even though ETF ownership may look passive, it can contribute to price informativeness.

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Appendix

A1 Alternative samples — parallel trend

Table A1.1: Dynamic effects of the introduction of ETF options on the preemption of earnings news: alternative treatment groups

The table reports the dynamic effects of ETF option inception on the preemption of earnings news. I use the samples from Table 4.6 and further require that all firms have observations for eight quarters before and after option inception dates. I estimate the effects using a modified difference-in-difference regression from Table 4.6, in which I replace the *Post* dummy with a series of dummy variables $Yr(k)$, where k takes values of (-2, -1, 1, 2) to indicate year-periods relative to ETF option inception. $Yr(-2)$ (indicating $[-2\ years, -1\ year]$ window) is omitted and serves as the baseline. I run the following regression:

$$Jump_{it} = \alpha + \sum_{k\in\{-2,-1,+1,+2\}} \beta_{1,k} Treat_i \times Yr(k)_{it} + \sum_{k\in\{-2,-1,+1,+2\}} \beta_2 Yr(k)_{it} + \beta_3 Treat_i + \beta_4 X_{it} + \theta_i + \theta_t + \varepsilon_{it},$$

the dependent variable, *Jump*, is the price jump ratio, as defined in Table 4.1. *Treat* is a dummy variable that equals one for the treatment group and zero for the control group. Treatment groups are defined in Table 4.6. Control variables include log of market capitalization, book-to-market ratio, and idiosyncratic volatility. I control for both ETF-stock and year-quarter fixed effects. Standard errors are clustered at ETF-stock level. t statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

Sample:	Relative spread		Option volume	
Dependent variable:	*Jump*			
$Yr(-1) \times Treat$	-0.0570	-0.0632	0.00696	0.00727
	(-1.26)	(-1.43)	(0.18)	(0.19)
$Yr(+1) \times Treat$	-0.141***	-0.147***	-0.114**	-0.111**
	(-2.83)	(-2.97)	(-2.34)	(-2.27)
$Yr(+2) \times Treat$	-0.154***	-0.144**	-0.109**	-0.106**
	(-2.79)	(-2.56)	(-2.09)	(-2.00)
$Yr(-1)$	0.0977***	0.0976***	0.0244	0.0295
	(2.92)	(2.85)	(0.73)	(0.87)
$Yr(+1)$	0.0757	0.0715	-0.00912	-0.00278
	(1.35)	(1.25)	(-0.16)	(-0.05)
$Yr(+2)$	0.147*	0.141*	0.00621	0.0143
	(1.77)	(1.65)	(0.07)	(0.17)
Controls	No	Yes	No	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
ETF-firm FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0181	0.0196	0.0201	0.0206
Observations	12419	12100	11471	11199

A2 Alternative weight cutoffs

Table A2.1: Impact of the introduction of ETF options on the preemption of earnings news: alternative weight cutoffs

This table repeats the difference-in-difference analysis on the impact of ETF option inception on the preemption of earnings news from Table 4.2 using alternative treatment and control groups. I use the sample from Table 4.2. Stocks with ETF-weight below 2% are assigned to the control group. For each of the three regressions, I assign stocks to the treatment group if their ETF-weight is above 2%, 3%, and 4%, respectively. The dependent variable, $Jump$, is the price jump ratio, as defined in Table 4.1. $Treat$ is a dummy variable that equals one for the treatment group and zero for the control group. $Post$ is a dummy that equals one for the two-year period after the pseudo-event date and zero for the two-year period before the pseudo-event date. Control variables include log of market capitalization, book-to-market ratio, and idiosyncratic volatility, which are defined in Table 4.1. I control for both ETF-stock and year-quarter fixed effects. The standard errors are clustered by ETF-stock. t statistics are reported in the parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels.

Cutoff:	2%	3%	4%
Dependent variable:		$Jump$	
$Post \times Treat$	-0.0520*	-0.0952**	-0.101
	(-1.90)	(-2.33)	(-1.40)
$Post$	-0.0444	-0.0448	-0.0491
	(-1.58)	(-1.49)	(-1.57)
Controls	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
ETF-firm FE	Yes	Yes	Yes
Adj. R^2	0.0174	0.0177	0.0185
Observations	14559	12313	11226