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Passive Investors and Market Reactions:

The Effect of ETF Ownership on Market Reactions to Earnings Announcements

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Preface and Acknowledgements

I was delighted to do this research on the effect of passive investors on market reactions to accounting information. Due to the relatively short existence of ETFs, research on the implications of this topic is scarce compared to other financial vehicles. I believe that this study contributes to a greater understanding of ETFs and that the findings of this study shed new light on the implications of ETFs.

With the help of my supervisor, Dr. J.J.G. Lemmen, I was able to conduct this study and his insights were of added value to me. Furthermore, I would like to thank the Datateam of the Erasmus Data Service Centre for their support in retrieving data.

Yours sincerely,

Jasper T.L. de Zwart

Abstract

Exchange Traded Funds (ETFs) have rapidly increased in both net assets value and in number. Investors who invest in ETFs do so as they prefer the passive characteristics of ETFs over actively managed mutual funds. Due to the passive characteristics of these investors, I expect that a greater presence of passive investors in a firm weakens market reactions to accounting information as passive investors are less interested in new information. This study tests that assumption by using 3,905 firm-quarterly earnings announcement observations. By using cumulative abnormal returns (CARs) and cumulative abnormal trading volumes (CATVs), I was able to measure the effect of ETF ownership on CARs and CATVs to earnings per share (EPS) surprises (proxy for accounting information) for every quarterly earnings announcement. The results of the tests provide evidence that ETF ownership does weaken the effect of EPS surprise on CARs and CATVs when CARs and CATVs are measured over a period of one trading day prior to the earnings announcement, the earnings announcement day itself and one post-announcement trading day.

Keywords: ETFs, Trading Volumes, Event Study, Panel Data Model, Earnings Announcements

JEL Classification: G12, G14, G15, C23

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1. Introduction

Passive investing becomes more and more popular among investors. It was not until 1993 that (small) investors were bound to pooling their cash into actively managed mutual funds. In 1993, the first exchange traded fund (ETF) was traded on the financial markets. This ETF, the SPDR (Standard & Poor's Depositary Receipts, which tracks the S&P 500 index), gave investors the opportunity to buy, with a limited amount of cash, one share of that ETF which held a portfolio of 500 different shares. Hence, investors are now able to diversify their portfolio by simply buying ETFs. Furthermore, passive investing is also the solution to the down part of its counterpart (read: active investing). Some well-known studies have shown that, on the long run, mutual funds (active investing) fail to systematically beat the market (Treynor & Mazuy, 1966; Jensen, 1968). When those studies were conducted, ETFs had not been invented yet. However, since 2003 there has been a rapid growth in the aggregated assets value of ETFs as well as the total numbers of ETFs. As of March 2017, the aggregated assets' value of ETFs has increased to 2.7 trillion U.S. dollars[1]. Moreover, according to the NYSE (2017), the consolidated ETF U.S. dollar volume represents approximately 30 percent of all issued U.S. stocks. Hence, ETFs have become an important new financial product and are still growing in assets value and in numbers.

Due to the growing interest in ETFs, research is necessary to better understand how ETFs affect the financial markets. As ETFs significantly rise in both volume and value, it is important for different parties (e.g. investors, regulators, firms etc.) to research the implications of ETFs. Since ETFs are a "young" investment vehicle, research on the effects of ETFs is relatively scarce compared to studies on other financial products. However, some studies already tackled some questions regarding ETFs. Glosten et al. (2016) found that an increase in ETF trading is accompanied by an increase in price information efficiency in the underlying stock, as reflected in the increase or decrease of a stock's return on earnings announcements. Da and Shive (2013) argue that ETF trading delinks fundamentals with stock returns, meaning that ETFs influence stock prices without fundamental changes to the value of the stock. Israeli, Lee and Sridharan (2016) stated that an increase of ETF ownership is accompanied by a decline in the informative pricing of the underlying securities.

This thesis relates, in a sense, to the work of Israeli, Lee and Sridharan (2016). They stated that ETF ownership is associated with a decline in the predictive power of current firm specific returns. The incentive for agents to trade on firm-specific information will decrease for firms that are widely held by ETFs. This implies that firm-specific information does not really matter anymore to passive investors. This might also imply that as a larger block of shares are held by ETFs, market reactions to accounting information might also be lower, as those passive investors do not trade on firm-specific information. To my knowledge, this implication of ETFs has remained to be tested. This thesis contributes to the

[1] Source: Investment Company Institute, April 26, 2017.

existing literature of ETF impact studies by examining the effect of ETFs on market reactions to accounting information. Hence, the main research question that this study tries to answer is:

Does a great presence of passive investors lower market reactions to accounting information?

To operationalize this concept and make it more suitable for statistical analysis, I use different proxies for passive investors and market reactions. As a way to measure the presence of passive investors I use ETF ownership of a specific firm and cumulative abnormal returns and cumulative abnormal trading volumes to capture market reactions around earnings announcements. Moreover, I use earnings per share surprises to measure the effect of the earnings announcement. I formulate one hypothesis (H1) to answer the main research question. Moreover, I will test this hypothesis in two ways (H1a and H1b). Note that all hypotheses are stated in the *null* form:

H1: There is no interaction between ETF ownership and market reactions to accounting information.

H1a: There is no interaction between ETF ownership and cumulative abnormal returns around earnings announcements.

H1b: There is no interaction between ETF ownership and cumulative abnormal trading volumes around earnings announcements.

The alternative hypothesis for the main research is that there is a negative interaction between ETF ownership and market reactions to accounting information. The alternative hypotheses for H1a and H1b would also be that there is a negative interaction between ETF ownership and cumulative abnormal returns and ETF ownership and cumulative abnormal trading volumes, respectively.

To test H1a and H1b I will use an extensive set of data that include different U.S. large cap firms and ETFs over a broad time period. This allows me to do panel data analysis and measure the causal effect of different variables by using cumulative abnormal returns and cumulative abnormal trading volumes (both include lags and leads). I will use OLS fixed effects regression models to estimate market reactions based on different variables, including ETF ownership and EPS surprises (a proxy to capture accounting information).

This thesis has the following structure; chapter 2 will cover the theoretical background, which includes the basic assumptions of the theories that I rely on. Moreover, it explains active and passive investing as well as the implications of ETFs. Chapter 3 discusses the data and methodology used for this research. Chapter 4 contains the results of the different statistical tests. Chapter 5 concludes and chapter 6 will discuss the limitations of this research and gives suggestions for future research.

2. Theoretical Background

This chapter consists of the theoretical background for this thesis. It specifically focuses on the two main areas of this research: market reactions and ETFs. The understanding of the former is essential for this thesis. Analyzing how markets react to information is what this research is after. Therefore, the theory of "efficient markets" will be explained in this section. Moreover, the implications of ETFs should also be investigated to get a clearer understanding of its impact on market reactions. Due to the importance of the two topics, this chapter will be split into the two previously described concepts.

2.1 Efficient Capital Markets

Decades ago, the general theory of the Efficient Market Hypothesis (EMH) was accepted by many academics in the field of economics and finance. The general idea of this theory is that stock markets are efficient, meaning that every piece of information is directly and fully incorporated into the stock price. In other words, every stock at every moment in time is traded against its fair value. Hence, according to the EMH, no one can achieve excessive returns on his or her trades. Outperforming the overall market is, according to the EMH, impossible.

Fama's (1970) work on the EMH was widely accepted by academics in the field of financial economics. Fama showed evidence for the EMH's different forms: 1) weak form, 2) semi-strong form and 3) the strong form, each will be briefly explained below.

- The *weak form* of the EMH supports the concept that common stock prices could be well approximated by evaluating historical prices.
- The *semi-strong form* of the EMH supports the concept that stock prices adjust when new public information (e.g. take-over bids, earnings announcements etc.) is available.
- The *strong form* of the EMH supports the concept that certain groups (inside managers, mutual funds etc.) have monopolistic access to information that is relevant for price development.

In his study, Fama tested the three forms of the EMH and concluded that there is extensive evidence in favour of the efficient market model. Many researchers agreed that the model of efficient markets hold.

Note that the EMH is associated with the idea of a "random walk", meaning that the stock prices follow a random walk and that tomorrow's price change will only reflect tomorrow's information. Moreover, tomorrow's price change is independent of today's price change. However, new information is by definition unpredictable and price changes are therefore unpredictable and follow a random walk (Malkiel, 2003). Although the EMH and random walk theory are generally accepted, some researchers question and criticize these theories. The EMH has been challenged by different economists that regard psychological and behavioral aspects of price determination. Furthermore, there are econometricians who believe that stock returns can be predicted to some extent. They argue that stock-prices can be predicted based on an analysis of past stock price patterns, also referred to as the "fundamental" analysis.

Some econometricians claim that investors could earn abnormal returns based on fundamental stock valuation. In this case, the econometricians point of view completely contradicts the believe that markets "fully reflect" all information (e.g. that markets are efficient).

The ongoing debate about efficient markets has received many new insights over the years and new argumentations were added to both sides. Malkiel (2003) examined the arguments against the EMH and concluded that the stock markets are even more efficient and less predictive than many papers would have us to believe. One remarkable argument that Malkiel used in favor of the EMH comes from Schwert (2003), who says that arbitrage strategies do not hold over a longer time period. Schwert found that those strategies hold in periods prior to its publication in academic journals and do not hold in periods after its publication. One reason for this might be that investors notice predictable patterns early on and exploit it to a certain point where this strategy is no longer profitable. In other words, arbitrage strategies lose their value when they become publicly known.

The EMH has been questioned over time, however Malkiel's survey is convincing when it comes to the EMH. Therefore, I rely on the theory of efficient markets as the foundation of this paper.

One important thing to mention is that the EMH only provides an abstract way of thinking when it comes to stock price changes, i.e. *all* information is incorporated in the price (this is a rather extreme definition). The EMH only gives us a general idea of how stock prices are adjusted by information. However, the EMH is based on different studies that do take a closer look at how news can change stock prices. These so-called "event studies" truly evaluate the effect of new information or events (e.g. earnings announcements or new product launches) on stock prices. Therefore, the next section will address more practical findings of how new information affects stock prices.

2.2 Market Reactions to Accounting Information

As explained earlier, event studies investigate reactions of dependent variables to explanatory variables. For this study, I will mainly look at event studies that evaluate market reaction to accounting information. The concept of market reactions can be operationalized by measuring stock prices (or price changes) and by measuring trading volumes. Event studies use different independent variables to measure or predict market reactions. Investor sentiment, for instance, can influence trading volumes. However, I am mainly interested in event studies that investigate the effect of accounting numbers on stock prices/trading volumes.

Accounting information, such as Earnings Per Share (EPS), dividends, growth rates etc., are important when it comes to firm valuation. The present value of a firm can be calculated by different models, e.g. discounted dividends, discounted abnormal earnings model etc. The dividend pay-out model is, however, only applicable to firms that do pay out dividends. An alternative way of calculating a firm's present value is by using the discounted abnormal earnings (Palepu et al., 2013). There are different valuation models, each with its own advantages and disadvantages, nevertheless, most of them rely on earnings numbers. Moreover, earnings numbers provide information of the firm's financial position and its content is considerable as more than one-half of all information about a firm is captured in that year's income numbers (Ball & Brown, 1968).

Accounting information is a significant driver of a firm's stock price and due to its relevance, accounting information (read: EPS/dividend/growth etc.) is considered to be very useful when comparing different firms. Analysts forecast, for instance, EPS numbers to support their buy/sell decisions (Palepu et al., 2013). Consensus forecasts are important for a lot of (small) investors, since they base their investment strategy on these forecasts. One can imagine that, when a firm does not meet its forecasted EPS, its stock price might drop down. What happens then is it that a firm gets "punished" by the market when it fails to meet its expected numbers. Nevertheless, this also works the other way around; firms get "rewarded" by the market when they overperform. Stock prices might go up (down) when the company overperforms (underperforms).

Campbell (1990), argues that unexpected stock returns must have a relation with changes in a firm's future position. He found that there is a positive relation between changes in the dividend-price ratio and abnormal stock returns. Fama (1997) also acknowledged that there is a positive relation between news and abnormal stock returns. He also claimed that overreactions are as common as underreactions to information. This implies that the market partially fails to incorporate all information into the stock price (if this was not the case, markets would not over- or underreact). Nevertheless, it is widely known that a firm's stock price reacts positively to earnings surprises, but it requires several quarters to fully reflect the information in the earnings (Kothari et al., 2006). However, some studies (Cready & Gurun, 2010; Kothari et al., 2006) show that there is a negative correlation between stock returns and earnings surprises at the aggregate level. Gallo et al. (2016) further investigated the prior finding and concluded that aggregate earnings convey policy news (Fed's policy actions) and that markets react negatively to unexpected policy changes. They argue that this is the main reason that drives the negative relation between aggregate earnings and returns. Although they found a negative association between aggregate earnings and returns, they agree that stock markets react positively to earnings surprises at the firm level.

An alternative proxy for market reactions is looking at trading volumes. There is a vast quantity of studies that examine the effect of earnings surprises on trading volumes. Basic trading volume theory relies on the assumption that investors (or traders) frequently revise their opinion about certain firms. Exchange occurs when investors assign different values to assets or firms (Karpoff, 1986). Hence, investors revise their opinion on assets when new information is available and each investor might assign different values to assets, based on new information. Therefore, we can expect abnormal trading volumes in post-event periods compared to pre-event periods.

Bamber (1987) researched the effect of earnings surprises on the magnitude and duration of trading volumes. Her research was based on data covering approximately 900 quarter earnings announcements by 195 listed firms over a period from January, 1977 until April, 1981. In her study, she controlled for firm size, as she claims that firm size is a factor affecting the availability of pre-disclosure information. Firm size might hold information prior to the earnings announcement, whereas earnings surprises are only observable at the specific moment of the earnings announcement. However, after controlling for firm size, she still finds evidence that earnings surprises are positively correlated with the magnitude and duration of trading volumes.

Other researchers (Maddala & Nimalendran, 1995) claim that prior empirical work, that measured the effect of earnings surprises on trading volumes, consists of substantial errors in variable biases and that this might lead to insignificant results. They argue that these errors are the results of using OLS estimates. Therefore, they applied the instrumental variable method as a different approach to test the implications of earnings surprises. They found significant effects of earnings surprises on price, trading volumes and bid-ask spreads. Using a different method, they still had results according to trading volume theory.

Many studies revealed that markets react (whether it is by price changes or trading volumes) to new information. New (accounting) information is absorbed by the financial markets and information influences investors when assigning values to assets. Thus, I find it reasonable to state that information does affect market reactions. For the second part of the theoretical framework, I will touch upon active investing vs. passive investing (or ETF trading). Combining the two (market reactions and passive investing) will provide sufficient background knowledge to successfully complete this research.

2.3 Active vs. Passive Investing

Financial markets are places where people can invest their spare cash. Most people are not that familiar with investing, thus they buy shares of funds that manage their cash. That cash is managed in a portfolio of a (mutual) fund. There are different types of funds, but for this research I will briefly describe mutual funds and exchange-traded funds (ETFs). The two funds are different in terms of portfolio management, whereas mutual funds rely on active management, ETFs are basically passive investments and require no active portfolio management. The two funds will be explained in the following paragraphs of this section.

As described earlier, mutual funds are associations in which a number of persons can pool their cash to be invested in stocks. Mutual funds make it possible for shareholders to redeem their shares at the price of the current value of the fund’s portfolio. A mutual fund continuously offers new shares based on the current net asset value (NAV) of that share (Fink, 2011). Mutual funds allow investors to diversify their portfolio easily without buying separate stocks or bonds. They give small investors the chance to buy stocks of professionally managed portfolios of different stocks (industry, commodities etc.). The portfolio managers have different investing strategies, but base their strategy on information that they have. With this (accounting) information, they for instance buy undervalued stock and sell overvalued stock. This active management requires a lot of effort and it is thus expected that clients pay fees for this service. Nevertheless, clients are willing to pay fees as they expect to earn excessive returns, compared to the market index.

However, the professional portfolio management that mutual funds provide has received many critics from the academic world since the 1960s. Well known classic studies (such as: Treynor & Mazuy, 1966; Jensen, 1968) showed that the average mutual fund is not able to beat the market on the long run. This means that active portfolio management is not superior to passive investing (i.e. index trading).

ETFs, as the name suggests, are also funds where investors can pool their money. Unlike mutual funds, ETFs can be traded throughout each trading day on stock markets. ETFs track a specific portfolio of stock, bonds, commodities etc. and its NAV is a close approximation of the value of the underlying assets. The price of an ETF is very close to the value of its underlying assets due to the ETF creation/redemption structure. An Authorized Participant (AP), in most cases a large financial institution, can submit an order for more shares. After the AP transferred the creation basket to the ETF, the AP receives new shares of that ETF (note that this can only be done once a day, at the end of each trading day). The AP can now hold on to those shares, sell it to clients or trade it in secondary financial markets. Redeeming shares goes the other way around. Hence, the ability of APs to create or redeem ETF shares at NAV promotes the ETF to track the underlying value of its assets. When there are discrepancies between an ETF's market value and the market value of its underlying assets, trading can align the ETF back to the value of its basket of securities. For instance, when the ETF is undervalued (compared to the market value of the underlying assets), investors are willing to buy the ETF. This increases the demand in the shares of the ETF, ultimately pushing up the market value of the ETF. This works the other way around when ETFs are overvalued compared to the market value of the underlying assets (Antoniewicz & Heinrichs. 2014).

Trading in ETFs can be very interesting for investors who are not willing to invest in actively managed funds. ETFs give an investor the possibility of passive investing, e.g. he/she does not have to process new available information about a specific firm. Since the ETF tracks an index that contains a lot of firms, firm-specific information is not relevant for the ETF investors. For example, one can buy shares of SPDR (Spider S&P 500 ETF) and track the S&P 500 index that contains 500 US large cap stocks. Firm specific information about one firm does not really matter, as the investor now holds 500 different stocks with only one share of SPDR S&P 500 ETF. The diversification possibilities of ETFs are also a great advantage of passive investing. An investor can buy 500 different stocks with only one ETF share. However, one can also buy shares of a mutual fund that diversifies its portfolio. This implies that the mutual fund's management has more stocks in its portfolio, thus it leads to more effort due to the fact that more information needs to be processed, resulting in higher fees. This difference can be observed when comparing expense ratios between ETFs and mutual funds, actively managed mutual funds have a higher expense ratio when compared to its passively managed counterpart, ETFs.

Many investors are interested in ETFs and its popularity still increases overtime. Since the beginning of ETFs in the 90s, ETFs have grown into a significant financial vehicle. Although ETFs remained relatively small until year-end 2003 with a total net assets of USD 151 billion and a total of 119 ETFs (Antoniewicz & Heinrichs, 2014), its total assets value increased and the total number of ETFs increased to USD 2,744.5 billion and 1,740 respectively as of March, 2017[2].

2.4 Implications of ETFs

Research in the field of ETFs is still very scarce compared to other financial vehicles, due to the fact that ETFs are relatively young funds. Moreover, empirical research on ETFs is limited to start their data timespan in 2003, as the presence of ETFs prior to 2003 is too small for empirical tests. Although, there is only a handful amount of studies I will briefly touch upon the main findings of these studies below.

Wurgler (2010) reviewed the different aspects of how ETFs have distorted the capital markets. The main critique on ETFs comes from academics and regulators who found that ETFs lead to increased volatility, systematic risks etc. However, in the absence of ETFs, investors have to assess all the individual information for each individual stock they hold. Doing this is a timely matter and, as a result, information might not be reflected in some segments of the market (Glosten et al., 2016). When investors have access to a basket of securities (i.e. in the presence of ETFs), information could be reflected in a timely manner for a cross-section of stocks. Glosten et al. (2016) found that an increase in ETF trading is accompanied by an increase in price information efficiency in the underlying stock, as reflected in the increase or decrease of a stock's return on earnings announcements. Their findings are only applicable to smaller sized firms and do not hold for the upper 50th percentile of the S&P 500 index firms. Ben-David et al. (2014) found that ETFs increase volatility and introduce new noise to the market.

On the other hand, ETF trading could also transmit systematic information (such as sentiment), resulting in non-fundamental shocks. This implies that ETF trading delinks fundamentals with stock returns (Da & Shive, 2013). For instance, a large sell order of an ETF might drive down the underlying price of the securities. This decrease in stock price is therefore not attributed to fundamental (i.e. accounting information), but is rather the result of a non-fundamental shock. Israeli, Lee and Sridharan (2016) found that an increased ETF ownership is associated with an increase in the co-movement of firm specific returns, a decline in the number of analysts covering the firm and a decline in the predictive power of current firm specific returns. In other words, an increase of ETF ownership is accompanied by a decline in the informative pricing of pricing the underlying securities.

[2] Source: Investment Company Institute, April 26, 2017.

3. Data and Methodology

This chapter addresses the data and research method in different sections. The first part, sample data, describes the period, sample firms, dependent and independent variables used for analysis and the sources (an overview of variables can be found in appendix A). The second part gives an overview of the variables and the third and last section of this chapter touches upon the statistical methods used to test the hypotheses.

3.1 Sample Data

First, I needed to select a specific timeframe to base my research on. ETFs are relatively new financial products, meaning that setting the right starting date for is crucial in order to get reliable statistical data. The first ETF was launched in 1993, however ETFs remained to have small Assets Under Management (AUM) compared to the aggregate financial markets. The popularity of ETFs increased over time as well as their AUM and ETFs have started to play a big role in financial markets nowadays. Until 2002, the presence of ETFs remained neglectable and most ETF studies use the year 2002 as the start point of their time period. Ben-David et al. (2014) started his time period in 2002 and Glosten et al. (2016) picked 2004 as their starting year. Glosten et al. noted that ETF ownership remained below 1% prior to 2004, however, I will use 01/01/2003 as my base period as more ETFs were added to the financial markets in 2003 compared to 2004. I set 31/12/2016 as the end date of my period, since financial information (holding information of ETFs, EPS etc.) of 2017 might not be available for all firms.

The sample includes 71 U.S. large capital firms from the S&P 100. These firms have major public exposure and have greater analysts' coverage compared to smaller firms. Smaller firms have less analysts' coverage, meaning that less EPS numbers for that firm are forecasted. I started with all S&P 100 firms (as of 31/12/2016) and I dropped firms from the sample that: missed daily observations of variables (returns, trading volumes etc.) and that missed EPS actual and forecasted numbers. After apply the prior conditions, 71 firms remained in the sample.

Daily information of those firms was retrieved from the Center for Research in Security Prices (CRSP). The following variables were retrieved from CRSP: bid price, ask price, trading volume, shares outstanding and returns without dividends. Quarterly estimates of EPS and actual EPS numbers were obtained from the Institutional Brokers' Estimate System (IBES) summary history database. The IBES summary history file contains means and standard deviations (SDs) of estimates as well as forecast dates and announcement dates. Mean estimates were extracted to compute EPS surprise and SDs of estimates were added to the variable list as SDs measure the power and uncertainty of EPS estimates. When extracting the data from IBES, I used a Forecast Period Indicator (FPI) of 6, which is the estimate that has been computed for the current quarter. Using other FPIs (FPI is the gap between the estimation date and the actual date of the announcement) will lead to different estimate values that might be less accurate as there is a greater gap between the forecast date and the actual date. Therefore, FPI 6 (estimate for current quarter) is more reliable as the time gap between the date of the estimation and actual announcement date is smaller compared to other FPIs. For this reason, I use FPI 6 estimates as they can be seen as the most accurate FPI (due to a smaller gap between estimation date and actual announcement date compared to other FPIs) and return the most recent estimate for quarterly EPS numbers. Daily U.S. 10-year Treasury bill interest rates were retrieved from Datastream (this variable was extracted to control for competition effects between the stock and bond markets). As a general rule of thumb: higher risk-free rates (in this study U.S. 10-year Treasury bills) increase the net present value of newly issued bonds, this makes bonds more interesting for investors. On the other hand, when risk-free rates decrease, the net present value of newly issued bonds decrease. Hence, when risk-free rates decrease, bonds become less interesting for investors as lower returns can be realized. This increases the interest in the stock markets as stocks have greater returns.

Next, ETFs needed to be selected for this study. I used the ETF screener & database tool from etf.com. There, I filtered on U.S. ETFs in all segments, with asset class: equity. This resulted in a list of 567 ETFs, next I looked up their CRSP Portfolio number and dropped 152 ETFs as they were not present in the CRSP Mutual Fund database. This resulted in a list of 415 ETFs that was suitable for my research. Using the CRSP Mutual Fund Portfolio Holding database, I was able to extract monthly holding data of the ETFs. I used the conditional statement tool where I set the security ticker equal to the 71 firm tickers. However, the CRSP Mutual Fund database occasionally lacked monthly holding information, leading to gaps in the timeline. I corrected for missing values by taking the last known number of shares of a firm for the month with the missing value. For instance, ETF x held 1,000 shares of ORCL in March 2006, 2,500 shares of ORCL in May 2006, but CRSP failed to record the number of shares of ORCL in April 2006. To overcome this problem, I took the number of shares invested in ORCL in March 2006 and applied it to the missing month of April 2006. When applying this technique, the number of shares of ORCL in the portfolio of ETF x is: 1,000 shares in March 2006, 1,000 shares in April 2006 and 2,500 shares in May 2006.

3.2 Computed Variables

To make the data suitable for analyses, I needed to compute new variables based on the extracted data. To control for bid-ask spreads on trading volumes, I calculated the bid-ask spread as the difference between the ask and bid price of a stock at time t divided by the ask price of that stock at time t. Next, the trading volume variable was converted to a relative trading volume variable (which makes it possible to compare trading volumes of firms) by dividing the number of shares traded of a firm at time t by the total shares outstanding of that firm at time t.

Market capitalization numbers were calculated as the product of a firm's stock price at time t and its shares outstanding at time t. The market cap variable was added to control for the effect of firm size on trading volumes. Bamber (1987) found that smaller firms show, on average, a greater increase of trading volumes after earnings announcements. She explained that pre-disclosure information for larger firms is presumably available, whereas smaller firms are less likely to be preempted by pre-disclosure information.

EPS surprises were calculated as the difference between the actual EPS of a firm at time *t* and the IBES mean forecasted value of EPS of that firm at time *t*, divided by the absolute forecasted value of EPS of that firm at time *t*.

ETF ownership was computed as the sum of shares of a specific firm over all ETFs at time *t*, divided by the shares outstanding of that firm at time *t*:

$$ETF\ ownership_{it} = \frac{\sum_{j=1}^{J} Number\ of\ shares\ held_{ijt}}{Number\ of\ shares\ outstanding_{it}}$$

Where, the sum of shares of firm *i* held by ETF j at time t is divided by the total number of shares outstanding of firm *i* at time *t*.

Market reactions are a rather vague concept and are only observable through abnormal figures of two measurable variables: returns and trading volumes. Abnormal returns (ARs) and abnormal trading volumes (ATVs) are generally used in research to measure market reactions. However, there is no standardized framework or theoretical model that prescribes how abnormal returns and abnormal trading volumes should be computed (Bamber et al., 2011). There are "simple" models that only look at mean numbers of that variable over a past period (estimation window). There are also models that follow a similar construction of the CAPM-model, which include market risks (market models). For this research, I use the market model which includes a single factor (linear model) to measure the firm's sensitivity to the overall performance of the market. I use the S&P 500 index as the market baseline as this index incorporates more firms compared to the S&P 100 index and therefore allows for a more complete illustration of the overall market performance.

$$AR_{it} = Ret_{it} - (\alpha_i + \beta_i \times MRet_t)$$

Where, AR_{it} is the abnormal return of firm *i* at time *t*; Ret_{it} is the return of firm *i* at time *t*; α_i is the intercept of firm *i*; β_i is the slope coefficient of firm *i*; and $MRet_t$ is the market return of the S&P 500 index at time *t*.

The market model has also been used to compute ATVs for firms. However, this model does not include the market's overall trading volume. Instead, I used the mean of relative trading volume (RTV) of the 71 firms as a market baseline (since I was unable to extract trading volumes data from any source). The RTV is calculated as the number of shares traded of firm *i* at time *t* divided by the shares outstanding of firm *i* at time *t*. The mean aggregate RTV will be the mean of RTVs of all firms at time *t* divided by 71 (total number of firms in the sample). I use the result of that calculation as the market RTV at time *t*.

Furthermore, I used the natural logarithm of RTVs, as additional analyses showed that RTVs were skewed to the right. The log transformation was also used by Bamber (1987) as she found similar characteristics of RTVs.

$$ATV_{it} = Ln(RTV_{it}) - [\alpha_i + \beta_i \times Ln(MRTV_t)]$$

Where, ATV_{it} is the abnormal trading volume of firm *i* at time *t*; $Ln(RTV_{it})$ is the natural logarithm of the relative trading volume of firm *i* at time *t*; α_i is the intercept of firm *i*; β_i is the slope coefficient of firm *i*; and $Ln(MRTV_t)$ is the natural logarithm of the mean of relative trading volumes of the aggregate sample of 71 firms at time *t*.

ARs and ATVs only show values at specific trading days, meaning that they do not show results over a period of time. Literature on market reactions have shown that market fails to directly incorporate new information after its announcement. Furthermore, when information might leak prematurely and market reactions might be observable before the actual announcement date. For this reason, I used cumulative abnormal returns (CARs) and cumulative abnormal trading volumes (CATVs) as a proxy for market reactions. CARs are the sum of ARs of a firm over a predetermined period and CATVs are the sum of ATVs of a firm over a predetermined period. In order to pick the right time limits, I ran multiple analyses using CRSP's event study tool, which presented the following graph:

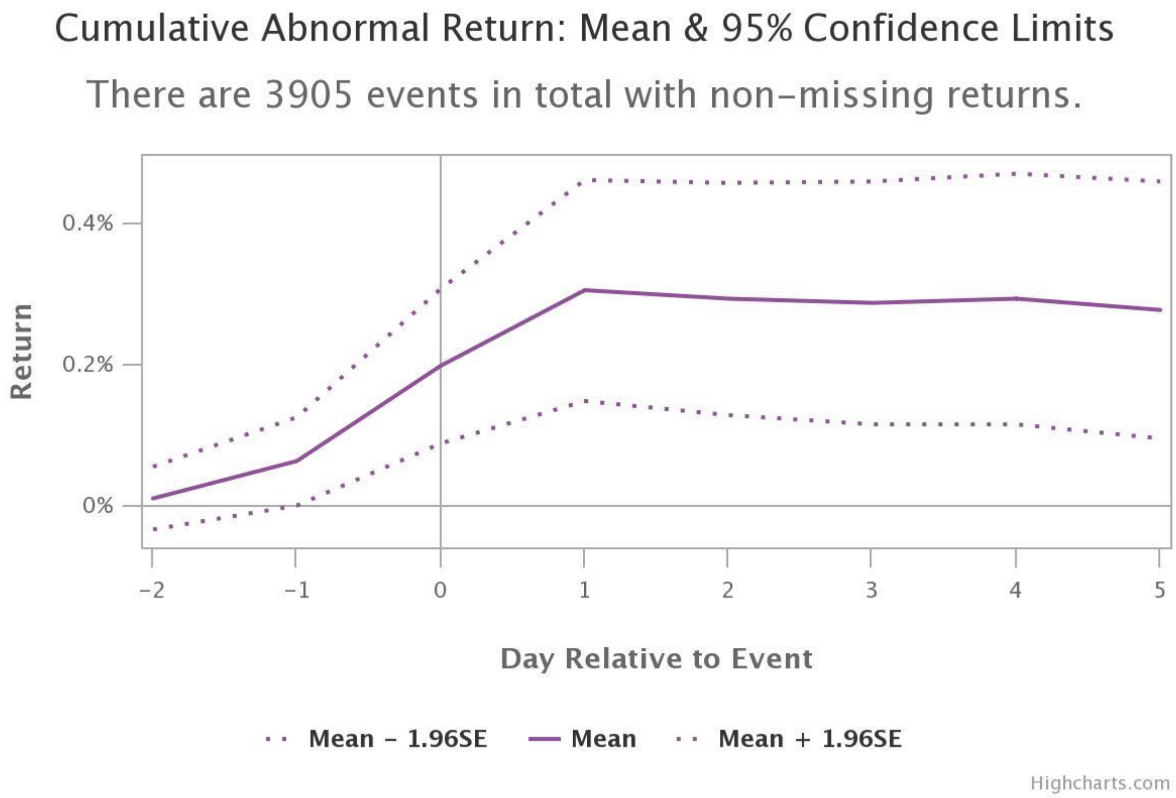

Figure 1. Graph of CAR with window: -2 trading days, +5 trading days

This graph illustrates CARs over time with 95% confidence limits. Moreover, the CAR after t+1 does not increase and stays relatively flat. The actual increase in CAR happens during t [-1,1], furthermore, two-sided t-tests showed that ARs were insignificant at the 5% at t-2, t+2 , t+3, t+4 and t+5. Due to the previously discussed findings, I set the interval for computing CARs and CATVs to [-1,1]. When applying this interval, the function of CAR and CATV can be written as follows:

$$CAR_{it} = AR_{it-1} + AR_{it} + AR_{it+1}$$

Where, CAR_{it} represents the cumulative abnormal return of firm *i* at time *t* and AR_{it} represents the abnormal return of firm *i* at time *t*.

$$CATV_{it} = ATV_{it-1} + ATV_{it} + ATV_{it+1}$$

Where, $CATV_{it}$ represents the cumulative abnormal trading volume of firm *i* at time *t* and AR_{it} represents the abnormal trading volume of firm *i* at time *t*.

According to the market overreaction literature, markets fail to respond to quarterly earnings announcement in a matter that fully reflect the time series of the announcement (Bartov et al., 2000). Bondt and Thaler (1985) found that markets overreact to unexpected and dramatic news events. This suggests that ARs and ATVs after undesirable news events are overstated, but the overreactions might ease off over time.

However, numerous studies found that post-earnings announcement drifts are indeed very real and this phenomenon is the most serious challenge to the EMH. After the first publication of the post-earnings announcement drift in 1968 (Ball and Brown, 1968), more and more studies are finding evidence for this concept. Ball (1978) addresses that at least twenty papers have found evidence of post-earnings announcement drift in the ten years after the phenomenon's introduction in 1968. More recent studies are still finding evidence of the post-earnings announcement drift of firm's reporting good (bad) news accompanied with positive (negative) abnormal returns over an extended period after the announcement date (e.g. Forner et al, 2009). Bartov et al. (2000) investigated the relation between institutional holders (whereas I use ETF ownership) and post-earnings announcement abnormal returns. They used an interval of [0, 59] to capture CARs for the post-earnings announcement drift. Their results indicated that there is a negative relation between institutional ownership and CARs during post-earnings announcement periods. Due to the many findings of post-earnings announcement drifts, I added two new dependent variables to measure CARs and CATVs during the period of one trading day prior to the earnings announcement (to capture possible information leaks) and 60 days after the earnings announcement (to include post-earnings announcement drifts). The two variables are written below:

$$CAR61_{it} = AR_{it-1} + AR_{it} + AR_{it+1} + AR_{it+2} + (\ldots) + AR_{it+59}$$

Where, CAR_{it} represents the cumulative abnormal return of firm *i* at time *t* and AR_{it} represents the abnormal return of firm *i* at time *t*.

$$CATV61_{it} = ATV_{it-1} + ATV_{it} + ATV_{it+1} + ATV_{it+2} + (\dots) + ATV_{it+59}$$

Where, $CATV_{it}$ represents the cumulative abnormal trading volume of firm *i* at time *t* and AR_{it} represents the abnormal trading volume of firm *i* at time *t*.

The 60 days after the actual announcement has not only been chosen as the cut-off point due to the approach followed by Bartov et al. (2000). The firms in my sample have to file their quarterly earnings to the U.S. Security and Exchange commission (using form 10-Q) within 40 calendar days after their fiscal quarter period (SEC, 2011). Moreover, data analysis showed that the minimum of trading days between earnings announcement was 62. Hence, setting the post-earnings announcement period to 59 days does not jeopardize the study as overlaps in post-earnings announcement period do not appear.

After computing all variables, daily firm-trading day observations that cannot be categorized as earnings announcement dates have been omitted from the sample. This means that the initial sample of 250,275 firm-trading day observations have been reduced to 3,905 firm-announcement day observations. The firm-announcement day observations contain values for the announcement day. I created a new time variable that expresses the announcement date's position in the new time variable. The new date variable is not equal to the trading day date, instead it is written as the quarter to which the earnings announcement was presented for. For instance, a firm presented its earnings for the second quarter of 2016 at July 20, 2016 (trading day); the new date variable for that specific trading day will be 2016-2. Note that I use quarter dates for the regression analysis instead of trading days. Firms within the same quarter-date time cannot be compared, since firms with the same quarter-date have observations from different dates. For example, firm x and y both share the same quarter-date: 2016-2. However, the values for firm x' variables might be of July 10, 2016, whereas firm y's observations might be of August 2, 2016.

3.3 Descriptive statistics

Independent variables (Bid-Ask spread, Ln (Market Cap), T-bill, ETF ownership, EPS surprise and SD estimate) and dependent variables (CAR3, CAR61, CATV3 and CATV61) that are used for statistical analysis are shown in table 1. As explained earlier, each variable has been measured for 71 firms for 55 quarter, leading to 3,905 firm-quarter observations.

There are no unexpected summary statistics for the variables, as I have dropped firms from the initial 100 firms sample (S&P 100 index) that had missing values and which had outliers. Also, note that the market cap variable has been transformed into a new variable Ln (Market Cap) since this variable was not skewed to the right according to its histogram (see appendix B). Applying the natural logarithm to market cap led to a distribution that is closer to normality.

Table 1. Summary statistics of relevant variables

Variable (Type)		Mean	Std. Dev.	Min	Max	Observations
Bid-Ask Spread (C)	overall	.0006284	.0012042	0	.0221774	N = 3905
	between		.0001942	.0003526	.0012778	n = 71
	within		.0011886	.0006495	.0218336	T = 55
U.S. 10-year Treasury (C)	overall	.0326853	.0107995	.0143	.0521	N = 3905
	between		.0001534	.0322782	.0330382	n = 71
	within		.0107984	.0141271	.0525071	T = 55
ETF Ownership (M)	overall	.0437792	.0236396	.0004805	.1561684	N = 3905
	between		.0059042	.0230085	.0569673	n = 71
	within		.0229009	-.010127	.1552685	T = 55
CAR3 (D)	overall	.0027235	.0485274	-.5305942	.4770948	N = 3905
	between		.0093378	-.0202004	.0564101	n = 71
	within		.0476332	-.5076703	.4234082	T = 55
CAR61 (D)	overall	.0010098	.103631	-.4996297	1.058692	N = 3905
	between		.0044087	-.0072307	.0113416	n = 71
	within		.1035385	-.5076564	1.051452	T = 55
CATV3 (D)	overall	.9527989	1.066573	-3.176152	6.520607	N = 3905
	between		.4347546	.0860874	2.446907	n = 71
	within		.9752846	-2.812009	5.591365	T = 55
CATV61(D)	overall	.2278972	14.44238	-58.94431	71.37682	N = 3905
	between		.5807845	-.9531359	3.216129	n = 71
	within		14.43086	-59.82154	71.89054	T = 55
EPS Surprise (M)	overall	.051014	.4183585	-8.320988	8.801587	N = 3905
	between		.0961537	-.4519875	.3543958	n = 71
	within		.4073158	-7.817986	8.527857	T = 55
SD Estimate (C)	overall	.0433212	.0545773	0	.7033333	N = 3905
	between		.0396318	.0035152	.1749697	n = 71
	within		.0378118	-.0902697	.6063969	T = 55
Ln (Market Cap) (C)	overall	17.91099	.9065286	13.18661	20.45456	N = 3905
	between		.7579651	15.91342	19.72963	n = 71
	within		.5052025	14.51666	20.10418	T = 55

Variable type refers to: control variable (C), dependent variable (D), main variable (M).

Correlations between variables can be found in table 2. This table shows that there are two independent variables which show multicollinearity when applying a threshold of 0.7 for the correlation coefficient. The two independent variables are U.S. 10-year Treasury and ETF ownership. Due to this multicollinearity concern, I would have to leave out the U.S. 10-year Treasury variable from the regression models.

Table 2. Pearson Correlation Matrix

	Bid-Ask Spread	U.S. 10-year Treasury	ETF Ownership	CAR3	CAR61	CATV3	CATV61	EPS Surprise	SD Estimate	Ln (Market Cap)
Bid-Ask Spread	1									
U.S. 10-year Treasury	0.2161	1								
ETF Ownership	-0.2155	-0.8127	1							
CAR3	0.0462	0.0413	-0.0241	1						
CAR61	0.0177	0.0469	-0.0505	0.4955	1					
CATV3	-0.0440	-0.0505	0.0733	-0.0090	0.0437	1				
CATV61	0.0081	0.0303	-0.0154	-0.0667	0.0066	0.6307	1			
EPS Surprise	-0.0191	0.0365	-0.0408	0.1815	0.0500	0.0156	-0.0463	1		
SD Estimate	0.0414	-0.1852	0.2104	-0.0395	-0.0123	-0.0583	-0.0214	-0.0189	1	
Ln (Market Cap)	-0.1614	-0.2330	0.2504	-0.1073	-0.1219	-0.1863	-0.1696	-0.0442	0.0350	1

3.4 Statistical Methods

The aim of this study is to test whether there is an effect of ETF ownership on market reactions to accounting information. Recall that market reactions are a result of new (accounting) information about a specific firm. Now, theory suggest that passive investors (read: people who trade in ETFs) do not base their investment strategy on new information. Active investors, on the other hand, base their investment strategy on new information. Therefore, new information, such as EPS surprises, is relevant for active investors. However, ETF ownership numbers have increased over time, meaning that a greater percentage of a firm's shares outstanding are held by ETFs. Due to the increase of ETF ownership, I expect that market reactions to earnings announcements have decreased. I will use four different Ordinary Least Squares (OLS) regression models to test whether my assumption holds. The first two models incorporate CARs as a proxy for market reaction and the last two models incorporate CATVs has a proxy for market reaction. CARs and CATVs are based on CAR3 and CATV3, resp. Furthermore, to take market overreactions and post-earnings announcement drifts into account, CAR61 and CATV61 are also predicted based on OLS regression. I also include firm-specific Fixed Effects (FE) as I use panel data for this research. The four OLS FE models are as follows:

$$\begin{aligned} CAR3_{it} = \alpha + \beta_1 EPS\ Surprise_{it} + \beta_2 ETF\ Ownership_{it} \\ + \beta_3 EPS\ Surprise_{it} \times ETF\ Ownership_{it} + \beta_4 SD\ Estimate_{it} \\ + \beta_5 Ln(Market\ Cap)_{it} + FE_i + \varepsilon_{it} \end{aligned}$$

$$\begin{aligned} CAR61_{it} = \alpha + \beta_1 EPS\ Surprise_{it} + \beta_2 ETF\ Ownership_{it} \\ + \beta_3 EPS\ Surprise_{it} \times ETF\ Ownership_{it} + \beta_4 SD\ Estimate_{it} \\ + \beta_5 Ln(Market\ Cap)_{it} + FE_i + \varepsilon_{it} \end{aligned}$$

$$\begin{aligned} CATV3_{it} = \alpha + \beta_1 |EPS\ Surprise_{it}| + \beta_2 ETF\ Ownership_{it} \\ + \beta_3 |EPS\ Surprise_{it}| \times ETF\ Ownership_{it} + \beta_4 SD\ Estimate_{it} \\ + \beta_5 Ln(Market\ Cap)_{it} + \beta_6 BidAsk\ Spread_{it} + FE_i + \varepsilon_{it} \end{aligned}$$

$$\begin{aligned} CATV61_{it} = \alpha + \beta_1 |EPS\ Surprise_{it}| + \beta_2 ETF\ Ownership_{it} \\ + \beta_3 |EPS\ Surprise_{it}| \times ETF\ Ownership_{it} + \beta_4 SD\ Estimate_{it} \\ + \beta_5 Ln(Market\ Cap)_{it} + \beta_6 BidAsk\ Spread_{it} + FE_i + \varepsilon_{it} \end{aligned}$$

I expect EPS Surprise to have a positive sign as positive earnings surprises tend to increase CARs both short-term and long-term due to post-earnings announcement drift (Bartov et al., 2000; Ali et al., 2007; Forner et al, 2009 and Konchitchki et al., 2010). Further, I expect a negative sign for the interaction term EPS Surprise × ETF Ownership as I assume that that passive investing characteristics of ETF traders lower the sensitivity of market reactions to EPS surprises. Ben-David et al. (2014) found that stocks with higher ETF ownership display higher volatility. However, they did not provide whether a higher ETF ownership increase or decrease price changes, only that it leads to a higher volatility of the stock. For this reason, the sign of ETF ownership is ambiguous.

Since SD in the consensus EPS forecast determine the power and relevance of the EPS estimate, I assume that CARs and CATVs are directly affected by the SD Estimate variable. I expect a negative sign as a greater SD Estimate implies a lower power of the EPS estimate itself, meaning that a greater SD Estimate leads to a lower CAR and CATV. Ln (Market Cap) is expected to be negative as Bamber (1987) found a negative relation between CATVs and firm size, she explained that smaller firms are less likely to leak information prematurely. Hence, larger firms tend to have smaller market reactions around earnings announcement as most information might already have been exposed. Lastly, Bid-Ask spreads indicate the level of disagreement between the buyer and seller. Thus, I expect the Bid-Ask spread variable to have a negative sign as a greater spread (i.e. greater disagreement) lower the number of traded shares, thus lowering CATVs.

4. Results

This chapter is set up into different parts, each part containing its own dependent variable: CAR3, CAR61, CATV3 and CATV6. The final part of this chapter includes an overview of all models.

4.1 Cumulative Abnormal Returns over a Three-Trading Day Period

Regression results for CAR3 can be found in table 3 function 1. All actual signs correspond with the expected signs that have been assigned to the variable. EPS Surprise is significant at the 1 percent level, meaning that CARs (trading day window: [-1,1]) are strongly influenced by EPS Surprises. For instance, when a firm reported an EPS of USD 50 and the EPS estimate was USD 25, there would be a EPS Surprise of 1, leading to an increase of CAR3 by 3.5%. This market reaction is weakened by the interaction term as this term has a coefficient of -0.281 and is significant at the 1 percent level. The coefficient seems like a rather big number, however, ETF Ownership is expressed with limits (0,1). When a firm has a EPS Surprise of 1 and an ETF Ownership of 8.5% (i.e. 0.085), its interaction term will lower the CAR3 by 2.4%. When solely analysing ETF Ownership, we can observe that its effect is significant at the 5 percent level. The magnitude of the direct effect of ETF ownership on CAR3 would be very small as table 1 showed that the mean value of ETF ownership is 0.04, resulting in a positive effect on CAR3 of 0.264% (0.04×0.066).

The control variable SD Estimate has a coefficient of -0.050 and is significant at the five percent level. This means that a higher SD Estimate directly lowers CAR3, since a higher SD Estimate indicates a weaker EPS forecast. When the consensus EPS forecast has the highest strength (read a SD Estimate of 0), the SD Estimate variable will not lower CARs as the product of the term is zero. However, the weakest consensus EPS forecast (expressed in terms of SD Estimate) in this sample of .703 (see table 1) will lower CAR3 by 3.5%. The strength of the consensus EPS forecast is significant when calculating CARs. The scatter plot of CAR3 and SD Estimate (Appendix C, panel A), indicates that there is a downward sloping fitted line between the two variables. However, most SD Estimate observations are smaller than 0.3, meaning that there cannot be said much about the effect of larger SD Estimates on CARs as there are only a few observations in the higher SD Estimate levels.

The other control variable, Ln(market Cap), is significant at the one percent level and it has a negative sign, which indicates that the size of the firm has a negative effect on CAR3. The coefficient seems rather small, however, the effect of firm size on CAR3 is -0.143 for the firm with the largest market cap (which is 20.45 according to table 1).

Table 3. Results of OLS fixed effect model for dependent variables CAR3 and CAR61

Variables	Expected Sign	(1) CAR3	(2) CAR61	(3) CAR61
EPS Surprise	+	0.035***	-0.005	-0.008
		(0.005)	(0.012)	(0.012)
ETF Ownership	?	0.066**	0.290***	0.324***
		(0.032)	(0.084)	(0.084)
EPS Surprise × ETF Ownership	-	-0.281***	0.344	0.398*
		(0.098)	(0.212)	(0.211)
SD Estimate	-	-0.050**	0.134***	
		(0.022)	(0.047)	
Ln (Market Cap)	-	-0.007***	-0.052***	-0.050***
		(0.002)	(0.004)	(0.004)
Constant	?	0.122***	0.920***	0.877***
		(0.031)	(0.067)	(0.066)
Observations		3,905	3,905	3,905
R-squared		0.040	0.050	0.048
Adjusted R-squared		0.021	0.031	0.029
Number of firms		71	71	71
Firm-specific FE		YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.2 Cumulative Abnormal Returns over a Sixty-One-Trading Day Period

Function 2 and 3 in table 3 show the results of the regression models for dependent variable CAR61. Function 2 shows the initial regression equation. In this model, the control variable SD Estimate shows an unexpected sign. A possible explanation for the unexpected sign can be found in appendix C, panel B. This graph shows the fitted regression line of CAR61 and SD Estimate. The line stays relatively flat, meaning that there is a lack of correlation between the SD Estimate and CAR61. This can also be found in the table 2, which tells that the correlation between SD Estimate and CAR61 is only -0.0123. Hence, the unexpected sign might be due to the very weak correlation and the fact that the distribution of SD Estimate is skewed to the left. Because of the SD Estimate's counterintuitive sign, this variable has been dropped from regression model, leading to function 3. The findings of function 3 are discussed below.

EPS Surprise seems to be negatively correlated with CAR61, meaning that positive earnings surprises lead to negative returns on a 61-trading day period. EPS Surprise is not significant, hence, the coefficient should be interpreted with caution. This insignificant result might indicate that, for this sample, the post-earnings announcement drift does not hold. However, testing the post-earnings announcement drift is not in the scope of this research and no critiques on this phenomenon can be derived from this study.

ETF ownership is significant at one percent level, and the magnitude of this variable is much greater compared to the CAR3 model due to the 61-trading day measurement period. The findings indicate that there is a direct effect of ETF ownership on CAR61. The interaction term, on the other hand, is only significant at the 10 percent level. However, EPS Surprise is insignificant and this might affect interaction term.

Function 3 is not a valid model in approximating CAR61 as it includes insignificant independent variables that have been selected for this research. Function 3 fails to reject the null hypothesis that the slope coefficient of the interaction term is equal to zero. However, this model should not be used in hypothesis testing as it includes insignificant independent variables.

4.3 Cumulative Abnormal Trading Volumes over a Three-Trading Day Period

Table 4 function 1 and 2 show the regression results for dependent variable CATV3. Note that function 2 leaves out the SD Estimate variable as this variable does not show significant results. Table 2 shows that there is a very weak correlation between SD Estimate and CATV3 and SD Estimate and CATV61 of -0.0583 and -0.0214, respectively. Moreover, as mentioned earlier, most SD Estimate observations are smaller than 0.3. Larger SD Estimate values are rare in this sample, meaning that nothing can really be said over larger observations and the effect of those. This variable has been dropped from function 1, due to the unexpected sign and the insignificant coefficient of SD Estimate. The findings of the new model (i.e. function 3) are discussed below.

The coefficients of all variables are significant at the one percent level, meaning that this is a very strong model. Moreover, all signs are as expected and comply with theory. The signs of the absolute EPS Surprise and the market cap are also found by Bamber (1987). How the sign and significance of ETF Ownership complies with theory will be discussed in section 4.5 as all models present a positive sign and statistically significant coefficients. The bid-ask spread's sign is positive and complies with the reasoning that a greater spread indicates a greater disagreement between buyer and selling. A greater disagreement between buyer and seller leads to fewer closed sales. The sign and coefficient of the bid-ask spread variable proof that this is indeed the case as a greater spread leads to less cumulative abnormal trading volumes. The interaction term is also significant, which means that the null hypothesis can be rejected that there is no interaction between EPS Surprise and ETF Ownership. In other words, based on the interaction term, it can be stated that ETF Ownership does indeed weaken the cumulative abnormal trading volumes over a three trading day period to EPS Surprises.

Table 4. Results of OLS fixed effect model for dependent variables CATV3 and CATV61

Variables	Expected Sign	(1) CATV3	(2) CATV3	(3) CATV61	(4) CATV61
| EPS Surprise |	+	0.440***	0.453***	3.317*	3.897**
		(0.121)	(0.120)	(1.755)	(1.745)
ETF Ownership	?	10.350***	10.469***	110.389***	115.828***
		(0.825)	(0.814)	(11.990)	(11.843)
EPS Surprise × ETF Ownership	-	-6.110***	-6.208***	-32.598	-37.082
		(2.107)	(2.104)	(30.610)	(30.595)
SD Estimate	-	0.394		18.046***	
		(0.442)		(6.427)	
Ln (Market Cap)	-	-0.627***	-0.618***	-11.628***	-11.209***
		(0.037)	(0.035)	(0.533)	(0.512)
BidAsk Spread	-	-42.385***	-41.044***	-399.499**	-338.052*
		(13.103)	(13.015)	(190.390)	(189.298)
Constant	?	11.724***	11.570***	202.898***	195.842***
		(0.641)	(0.617)	(9.307)	(8.970)
Observations		3,905	3,905	3,905	3,905
R-squared		0.090	0.090	0.123	0.121
Adjusted R-squared		0.072	0.072	0.105	0.104
Number of firms		71	71	71	71
Firm-specific FE		YES	YES	YES	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.4 Cumulative Abnormal Trading Volumes over a Sixty-One-Trading Day Period

The results of the regression model with dependent variable CATV61 can be found in table 4 function 3 and 4. The variable SD Estimate has been dropped from function 4 as the sign is counterintuitive. Function 4 shows that both the absolute value of EPS Surprise and ETF ownership are significant (P<0.05 and P<0,01, respectively). However, the term of interest (interaction term: EPS Surprise × ETF Ownership) is not significant. The market cap variable has a negative sign and is significant at the one percent level. This variable seems to be a strong control measurement in all models. The sign of the bid-ask spread remains negative, but it is not significant in function 4.

Based on the function 4, the null hypothesis cannot be rejected as the interaction term is not significant. Again, the sixty-one day model fails to reject the statement that ETF Ownership does not weaken abnormal trading volumes to EPS Surprises.

4.5 Aggregate Summary of the Regression Results

Both the preferred models of CAR3 (table 3, 1) and CATV3 (table 4, 2) show significant results. In both models, the actual signs of the variables correspond with the expected signs. The ambiguous sign of ETF Ownership turned out to be positive for both models. The significance of ETF ownership on CARs was also found by Ben-David et al. (2014) as they argue that a greater ETF ownership increases volatility. The effect of the absolute value of EPS Surprises and the effect of market cap on cumulative abnormal trading volumes was also found by Bamber (1987). She explains that larger firms have a harder time keeping earnings information secret until the announcement date itself. This leads to smaller abnormal trading volumes for larger firms as information about larger firms are typically leaked earlier (i.e. before the earnings announcement). The other two control variables, SD Estimate and bid-ask spread, were expected to be negative. However, the SD Estimate variable only proofed to be align with its expectation for the CAR3 model and failed to be aligned when looking at CAR61, CATV3 and CATV61. Bid-ask spread was only significant in the CATV3 model.

The term of interest (interaction term EPS Surprise × ETF Ownership) is negative and significant in the two market reaction models. Based on the findings of CAR3 (1) and CATV (2), we can reject the null hypothesis that there is no effect of ETF ownership on market reactions to accounting information. The models show that there is a significant impact of ETF ownership on both CARs and CATVs over a period of three trading days [-1,1].

Alternatively, we cannot confirm that ETF ownership does lower market reactions to accounting information as CAR61 (table 3, 3) and CATV61 (table 4, 4) do not show significant coefficient for the interaction term. In addition to that, CAR61 (3) should not be used as EPS Surprise is not significant. However, one should consider that the insignificant results of the 61-trading day period might be due to omitted events. I did not control for events that might influence CARs and CATVs during the 59 trading days after the earnings announcement. Using a three-trading day period is more reliable as no intermediate events (events that might happen during the 59 trading days after the earnings announcement) can influence the CAR and CATV. For this reason, I argue that the power of the significant results of the CAR3 and CATV3 model outweigh the smaller power of the insignificant results of the CAR61 and CATV61 model.

5. Conclusion and Implications

According to the EMH, new information is directly incorporated in a firm's stock price. Whenever new information arises, investors react to this piece of information as new information signals future firm performance. Generally, these market reactions can be observed by looking at abnormal returns and abnormal trading volumes. Active investors are very interested in new information as they continuously try to beat the market by buying undervalued and selling overvalued stocks. Its counterpart, the passive investor, should be less interested in new information as he does not "bet" on the market's misinterpretation of a firm's stock price. Instead, passive investors stall their cash in ETFs and typically hold on to them for a longer period. Due to the relatively small incentive of the passive investor to continuously monitor the news for new information, we should observe lower market reactions for firms who are partially owned by passive investors. I assume that accounting news does not encourage passive investors to act on that event, resulting in lower aggregate market reactions to that event. This resulted in the following null hypothesis: ETF ownership does not affect market reactions to accounting information. The alternative hypothesis would be that ETF ownership lowers market reactions to accounting information. I was able to test the null hypothesis by using a sample of 3,905 firm-quarter observations. The difference between a firm's actual EPS and its forecasted EPS was used to measure EPS surprises. ETF ownership (total of shares held by ETFs / total shares outstanding) was used as a proxy to measure the presence of passive investors of a firm. Market reaction was expressed into two measurable variables: abnormal returns and abnormal trading volumes. Multiple OLS fixed effects models were executed and the results provide evidence that the null hypothesis can be rejected. The statement that a greater presence of passive investors lower market reactions can be accepted. However, the results were only significant when looking at cumulative abnormal returns and cumulative abnormal trading volumes over a period of three trading days [-1,1], where $t = 0$ is the earnings announcement day. Models that incorporated cumulative abnormal returns and cumulative abnormal trading volumes over a period of sixty-one trading days [-1,59], where $t = 0$ is the earnings announcement day, do not show significant results. The 61-trading day period was added to incorporate the post-earnings announcement drift phenomenon. However, the models did not show significant results. The reason for this might be that the model did not control for other news events during the post-earnings announcement period of fifty-nine days. Therefore, the 61-trading day period model is inferior to the 3-trading day period, as the 3-trading day measuring period does not suffer from omitted news events. For this reason, I argue that this study provides enough evidence that a larger presence of passive investors weakens market reactions to accounting information, based on a three-trading day measuring period.

The results indicate that passive investing has some implications. The most important one is that markets do not correctly react to earnings announcements as a greater presence of passive investors lowers market reactions. ETFs basically weakens market reactions to new accounting information.

Other studies (e.g. Ben-David et al., 2014; Israeli et al., 2016) also found that a greater presence of ETFs delinks market reactions from its fundamentals and that ETFs add noise to the financial markets.

6. Limitations and Future Research

There are several limitations to this research that might influence the power of the tests and the validity of the variables. The sample is based on 71 S&P 100 firms, meaning that these firms have different characteristics compared to midcap and small cap firms. Therefore, the results are only applicable to S&P 100 firms and should not be generalized for the entire U.S. stock market. Furthermore, one should also take the unregistered ETF holding information into account when reading the results. As explained in chapter 3, some monthly ETF holding numbers were unregistered. I corrected for missing values by adding the holding information of the previous month into the month with the missing value. Hence, this does not illustrate the actual ETF holding information of that month, as it only is an approximation. Also note that during the 59 trading days after the earnings announcement, I did not control for other news events. This might have led to the insignificant findings of using the 61-trading day approach.

Future research could build upon this study by incorporating firm-specific news events to control for abnormal returns and abnormal trading volumes during a 61-trading day period. This might shed new light on the long-term effect of ETF ownership on market reactions to accounting information. Furthermore, such a study could also incorporate other accounting variables such as growth. Take Tesla, this firm makes losses every year however, its stock price has always stayed high. For investors in Tesla, they do not build their actions on earnings but on growth numbers as they believe that Tesla has great potential. Applying the results of this study to Tesla's earnings announcements would not make sense as EPS is not a measure investors base their decisions on.

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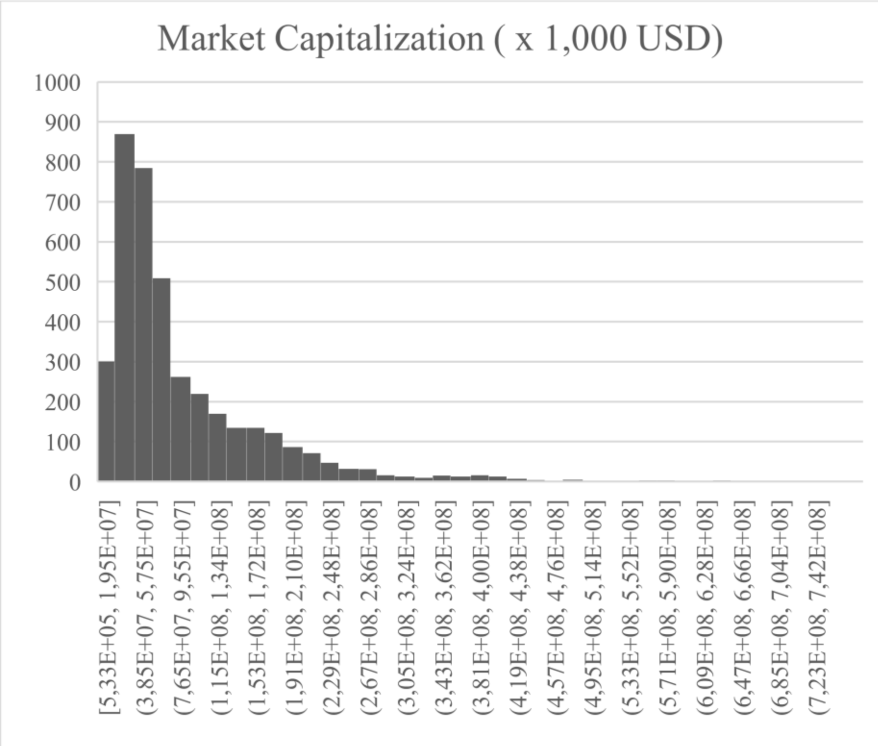
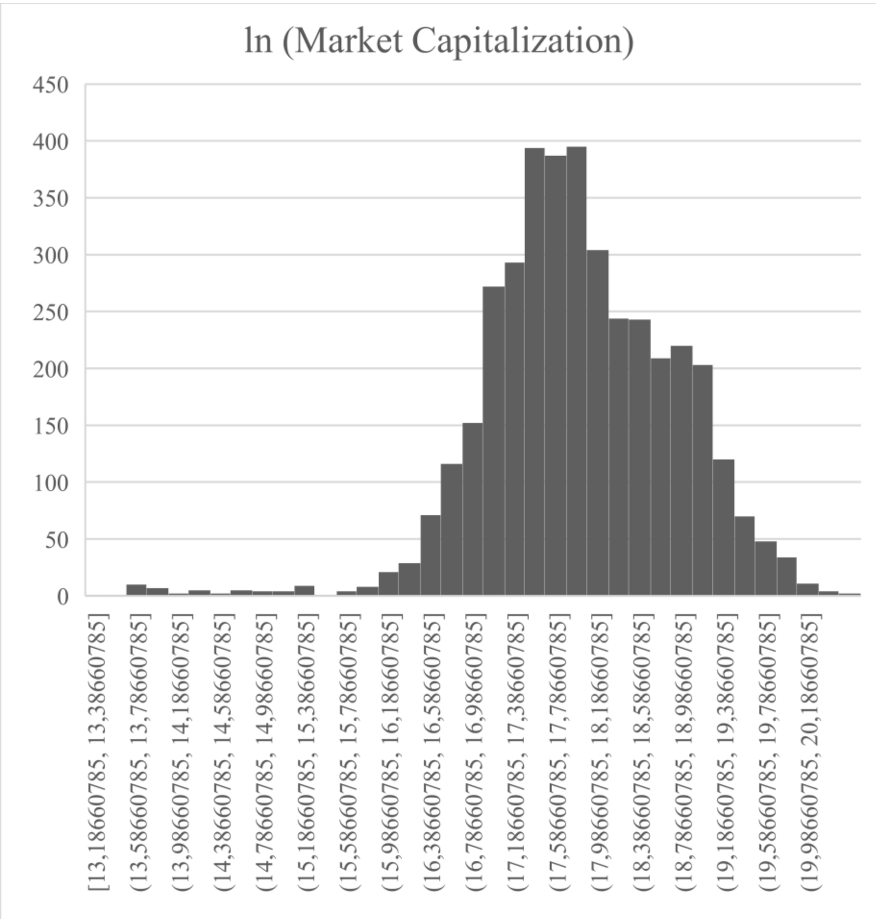
Appendices

Appendix A Abbreviations, Definitions and Sources of Variables

Abbreviation	Definition	Source
Bid-Ask Spread	This variable measures the difference between the bid and ask price of a stock. It is measured as the difference between the bid and ask price, divided by the ask price.	CRSP
U.S. 10-year Treasury	This variable measures the interest rate of a U.S. 10-year government bond.	Datastream
ETF Ownership	This variable measures the shares held by ETFs of a firm. It is calculated as the sum of number of shares held by ETFs of a specific firm divided by the shares outstanding of that firm	CRSP
CAR3	This variable measures the cumulative abnormal return of a stock over three trading days: t-1, t=0 and t+1, where t=0 is the earnings announcement day. The daily abnormal return is calculated based on a single factor model.	CRSP (daily returns)
CAR61	This variable measures the cumulative abnormal return of a stock over sixty-one trading days: t-1, t=0 and t+59, where t=0 is the earnings announcement day. The daily abnormal return is calculated based on a single factor model.	CRSP (daily returns)
CATV3	This variable measures the cumulative abnormal trading volume of a stock over three trading days: t-1, t=0 and t+1, where t=0 is the earnings announcement day. The daily abnormal trading volume is calculated based on a single factor model.	CRSP (daily trading volumes)
CATV61	This variable measures the cumulative abnormal trading volume of a stock over sixty-one trading days: t-1, t=0 and t+59, where t=0 is the earnings announcement day. The daily abnormal trading volume is calculated based on a single factor model.	CRSP (daily trading volumes)
EPS Surprise	This variable measures the difference between the actual earnings per share and the mean forecasted earnings per share of a firm. The difference between the two, divided by the mean forecasted earnings per share result in the EPS surprise.	IBES
SD Estimate	This variable measures the power of the mean forecasted earnings per share and it is simply the standard deviation of the forecasted earnings per share.	IBES
Ln(Market Cap)	This variable is the log transformation of a firm's market capitalization. The log transformation makes the market capitalization more suitable for regression.	CRSP (market capitalization)

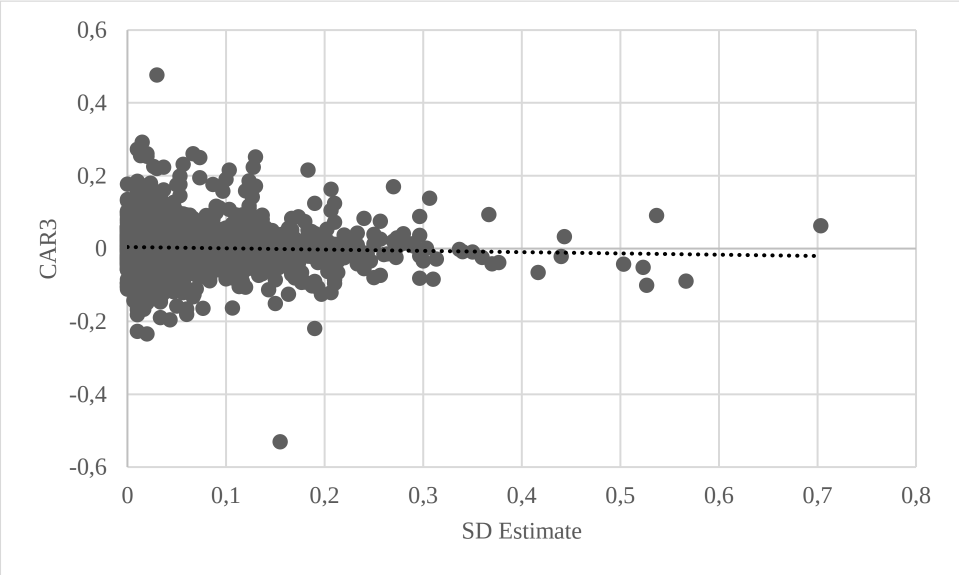
Appendix B Histogram of Market Capitalization and Ln (Market Capitalization)





Appendix C Scatter plot of CAR and SD Estimate

Panel A Scatter plot of CAR3 and SD Estimate with fitted linear regression line



Panel B Scatter plot of CAR61 and SD Estimate with fitted linear regression line