EVERYTHING IS RELATIVE

UNDERLYING MECHANISMS AFFECTING INVESTOR REACTIONS TO CONTRAST EFFECTS IN THE US FINANCIAL MARKET

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Everything is Relative: Underlying Mechanisms Affecting Investor Reactions to Contrast Effects in the US Financial Market

Abstract:

Contrast effects influence our perception of information because it biases us to perceive matters relative to each other and not by their absolute values. This paper explores contrast effects in a financial setting. Contrasts are measured by comparing earning news of firms with announcement dates following each other. We replicate and extend a study conducted by Samuel M.Hartzmark and Kelly Shue (2018) in which they find that contrast effects distort market reactions to firm earnings announcements in the US financial market. We study later years (1990-2020) and expand the sample size to also incorporate small firms and we find that investors' return reactions are biased by contrast effects. We extend the study to include tests of possible underlying mechanisms affecting reactions to contrast effects. First, we test if varying market conditions influence the effect. We find that for positive earnings surprises, reactions to contrast effects decrease as market strength increases and for negative earnings surprises, reactions to contrast effects increase as market strength increases. Second, we look at contrast effects in relation to behavioral psychology and find that the varying return response to previous days' earning surprises could be explained by investor loss aversion. After studying these potential mechanisms, the conclusion is that both factors influence investors' reactions to contrast effects.

Keywords:

Contrast effects, Prospect theory, Reference point, Earnings announcement, Earnings surprise, VIX, The relative level of market strength, Decision-making theory, Loss aversion

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I. Introduction

A contrast effect is a psychological bias that makes us judge matters relative to each other instead of individually. This is a natural human tendency since we often use benchmarks against which our emotions, performances, experiences, and other aspects of our lives are measured. For instance, it has been found that when individuals are exposed to extremely harsh crimes and then asked to choose the penalty for a lighter crime, the punishment is set lower compared to when individuals are first exposed to much milder crimes and then told to penalize the same crime (*Rodríguez & Blanco, 2016*). Not surprisingly, contrast effects also exist in assessment evaluation. In an experiment where clinicians viewed videos of good, mediocre, and poor performances in randomized order by first year doctors, when a good performance preceded a poor one, the ratings for the good performance topped those given by the control group who had not viewed the poor performance. Similarly, mediocre performances were rated lower when preceded by good performances than when only the mediocre performance was viewed (*Yeates et al, 2015*). Evidently, contrast effects rely on reference points as we make judgements based on deviations from such points. This has been studied in behavioral economics and psychology for decades and is often called reference dependency. Kahneman and Tversky discuss a model of reference dependency, namely prospect theory. Prospect theory states that individuals view outcomes as gains and losses rather than final states, where gains and losses are relative to a reference point (*Kahneman & Tversky, 1979*). This loss and gain outlook from the reference dependency theory can also be applied to contrast effects since a contrast can make matters appear better (a gain) or worse (a loss) than if the contrast had not been present.

This paper explores contrast effects in a setting not discussed above, namely in the financial market. We aim to replicate and extend the study *A Tough Act To Follow*, conducted by Hartzmark and Shue (2018) (below referred to as HS) in which they investigate if contrast effects exist in the US financial market and distort the return reaction to earnings announcements there. An earnings announcement is a public statement, usually every quarter, in which a company reports its earnings. The market reacts to these announcements because prior to a firm's earnings announcement, several analysts will have made predictions of what the firm's earnings will amount to. The analyst forecasted earnings serve as a reference point to which the actual earnings are compared. The difference between the firm's actual earnings and the analyst forecasted earnings are the unexpected earnings, often also referred to as an earnings surprise.

Market reactions to firm-specific earnings announcements have been explored in several previous studies. Ball and Brown (1968) were among the first to study earnings surprises and discovered that the market reacts differently to positive and negative surprises. A positive surprise is when the actual earnings exceed the forecasted earnings and a negative surprise is when the reverse is the case, actual earnings are below forecasted earnings. They found that positive earnings surprises result in an increase in returns while negative earnings surprises result in a decrease in returns. In later years, this study was replicated and extended by Craig and Wahlen (2004). They confirmed that annual stock returns are positively correlated to earnings surprises.

The positive relation between annual stock returns and earnings surprises is in accordance with rational theory since we assume that all assets are fairly priced and that the only thing the market should react to on the announcement day is the surprise. That is, the amount by which the actual earnings deviate from the forecasted earnings. In this sense, earning announcements represent the news to which the market reacts. The direction of the reaction depends on the contrast (good or bad) between the forecasted earnings (the reference point) and the actual earnings. One can broaden this context and, as in HS, instead of just looking at single firm-specific earnings surprises, look at whether firms' surprises yesterday affect the perception of other firms' surprises today. It is reasonable to assume that if investors read about a very large earnings surprise today, they will be disappointed if their companys' earnings surprise reported the day after is worse. As a result, if contrast effects exist in financial markets, the theory predicts that there is a negative relation between the earnings surprise the day before and the return reaction to the following day's earnings surprise (*HS, 2018*). In other words, if the earnings surprise the day before is positive, this will make the surprise the following day appear less favorable due to the contrast to yesterday's very good surprise, and returns should be lower. Similarly, if the earnings surprise the day before is poor, the surprise today will appear better by comparison, and returns should increase. Studying contrast effects in the financial market is of interest because the existence of such an effect means prices are distorted and that all assets are not fairly priced. The study is highly relevant because as HS finds and we replicate, contrast effects do affect prices of assets and thus describe a new form of mispricing. A mispricing not simply due to the lack of or concealed information (news) and the absolute content of these news, but from a bias created due to the perceived relativity of the news (*HS, 2018*).

The aim of this study is to determine if there are any underlying mechanisms influencing the return reactions to contrast effects in the US financial market. We follow the same procedure used in HS to first confirm that contrast effects in the US financial market persist when studying later years and a larger sample containing several small firms. It is especially interesting to see if contrast effects persist when incorporating small firms as they tend to get less attention from investors. Hypothetically, this could imply that the magnitude of investors' return reactions are lower. Similarly to HS, we also analyze reactions to firms' own surprise, taking into consideration if the previous days' surprises were more positive or more negative. This test is relevant since the theory of contrast effects predicts that the reaction to contrast effects is of greater magnitude when the previous days' earning surprise was negative (*HS, 2018*). After finding that contrast effects persist in later years and using a larger sample, we test two potential mechanisms underlying return reactions to contrast effects. More specifically, market strength and loss aversion. These have been studied in various contexts before. However, we have not found any previous studies that link them in an analysis of contrast effects. For this reason, and since these two underlying mechanisms could be active at the same time, it is relevant to incorporate them in a single study.

We begin the extension by analyzing if investors react differently depending on the prevailing level of market strength. Inspired by Conrad et al. (2002), who study if the markets' strength influences the return reaction to single firms' earnings news, we want to see if market strength influences investors' reactions to contrast effects. More specifically, we test if reactions differ in a strong, relative weak market. This is a topic of interest, especially now during the ongoing pandemic, when the market has been very volatile. It is reasonable to expect that investors are influenced by the markets' strength. More specifically, since investors tend to make extrapolative expectations, it is possible that the relative level of the market could initiate investor over or underreactions to earnings news (*Kewei et al. 2006*). A high relative market could lead to overconfidence amongst investors, thus high expectations for earnings and subsequent negative earnings surprise due to those expectations not being met. Alternatively, a low relative market could, using the same logic, lead to positive earnings surprises.

We proceed by testing if a psychological bias, namely loss aversion, is a mechanism underlying investors' reactions to contrast effects. The theory of loss aversion states that losses loom larger than corresponding gains (*Tversky and Kahneman, 1991*). This is a fascinating theory because it implies that we have an asymmetric response to gains and losses. Logically, we tend to enjoy gains while we do not like losses. However, this theory goes deeper than that and claims that we value gains less than what we despise losses. In our setting of contrast effects, this entails that investors will react stronger if previous days' earnings news were bad compared to if they were good. We explore if the varying return responses to previous days' surprises can be explained by investors being loss averse.

In terms of the results, from our baseline regression, we confirm HS' findings and show that investors react to contrast effects also in smaller firms. Moreover, similarly to HS, we find that return reactions to firms' own surprises are stronger when the previous days' surprises are more negative than more positive. With regards to the results of our extensions, we find that for positive earnings surprises, the return reaction to contrast effects decreases as the market strength increases and for negative earnings surprises, the return reaction to contrast effect increases as the market strength increases. Furthermore, we find that investors' reactions to earnings news are asymmetric and that this could possibly be explained by loss aversion.

II. Literature Review

The market's reaction to earnings announcements has been of interest to several researchers before and the effect these news have on returns has been studied in slight variations by many.

Ball and Brown (1968) were one of the pioneers in studying price reactions to firm's earnings announcements. They found that the market reaction differs depending on if the earnings surprise was positive or negative, where a positive earnings surprise triggered an increase in returns and a negative surprise led to a decrease in returns. Later, Ball, this time together with Shivakumar (2008), sought to quantify how large the influence of earnings announcements on returns is. Their study is meaningful since evidently there are various externalities that can affect returns. Moreover, since so many studies look at earnings announcements' impact on returns, it is highly relevant to assess how significant this impact really is. While Ball and Shivakumar (2008) found that earnings announcements far from explain the full return reaction, they found that four quarterly earnings announcements explain circa 6%-9% (1%-2% in annual terms) of the total information incorporated in the share price.

The research on return reactions to firm-specific earnings announcements is both vast and comprehensive. In later years, it appears as if researchers niche their studies on firm-specific earnings announcements in an attempt to discover new valuable findings. For instance, DellaVigna and Pollet (2009) also find that investors react positively to good earnings news and negatively to bad earnings news. However, digging deeper into these reactions, they compare investor reactions to weekday and Friday earnings announcements. They find that due to distractions and investor inattentiveness, investors' reactions to Friday earnings announcements are both delayed and an underreaction. Then, once investors realize the information they missed, they begin to trade and this powerful response reverses the previous underreaction. DellaVigna and Pollet's (2009) study is relevant to our study for two main reasons. First, they conclude that the day of the week influences the return reactions to firm-specific earning announcements which entails that there are underlying mechanisms that bias investors' perceptions of earning news. Second, it shows that return reactions depend on investors' attentiveness. This is relevant to our study since we incorporate small firms which generally receive less attention from investors. Thus, it is interesting to see how this affects investors' return reactions to contrast effects.

Deshpande and Svetina (2014) also narrow the focus of their earnings announcement study and look at local firm-specific return reactions to negative earnings surprises. Referencing several previous studies that find a positive relation between earnings surprises and returns, their study assumes this relation persists and they focus solely on negative earnings surprises. They compare negative earnings surprises today to the last-year same-quarter earnings and find that if the current earnings are higher than last years', the negative impact on returns is lessened. On the other hand, if the current earnings are lower than last years', the negative impact is heightened. Evidently, their study indicates that firms' historical performance influences investors' reactions and that historical performances serve as a reference point for how current earnings are perceived. This is an indication that reference points, consciously or not, play a key role in investor return reactions. Furthermore, reference points are a central element in our study since contrast effects build on comparisons against reference points.

Similarly to DellaVigna & Pollet (2009) and Deshpande & Svetina (2014), Conrad et al. (2002) differentiates their study on return reactions to firm-specific earnings announcements by incorporating market strength as an element. More specifically, they investigate whether the return reaction to good and bad firm-specific earnings surprises changes as the relative level of the market changes (market strength). They conclude that the reaction to negative earnings surprises increases with the market level, while for positive earnings surprises, they find that the return reaction decreases as the market level increases. This study is interesting because it could be evidence of a form of contrast effect for single firm earnings announcements. How so? Well, it is rational that if the market is strong, negative earnings news will appear worse than if the market is weak because the contrast will be greater. Applying similar reasoning to positive news, in a strong market, good earnings news do not differentiate as much from the reference point (the strong market) as if the market had been weak and thus the return reaction will be smaller.

Evidently, while a form of contrast effect could have been captured in the Conrad et al. (2002) study, HS extends previous studies by broadening the perspective from simply looking at the effect on returns that individual firm's earnings surprises has. Instead, they test and confirm that investors' return response to earnings announcements today is biased by yesterday's earnings news. The HS study is highly relevant to our study since before testing potential mechanisms underlying return reactions to contrast effects, we replicate HS to confirm that contrast effects persist in later years and using a larger sample.

Previous studies have shown evidence of external influences on investors' reactions. Conrad et al. (2002) show that market strength influences the return reactions to single firms' earning announcements. However, they have not studied this in the context of contrast effects. Since market strength is a potential factor that could affect the return response to contrast effects, it is interesting to investigate it as a potential underlying mechanism. Other research has found evidence of internal influences, for instance loss aversion. Bouteska and Regaieg (2020) find that loss averse investors negatively impacts US firm performance. Their findings indicate that loss aversion is a powerful bias with important consequences. This makes it relevant to investigate loss aversion in a contrast effect setting, specifically exploring if the varying return responses to previous days' surprises can be explained by investors being loss averse

IV. Data

A) Data Collection & Sample Selection

We use quarterly data between 1990-2020 on actual earnings and analysts' consensus estimates for US listed firms from *The Institutional brokers estimate system* (IBES). Further, we use daily stock price data and number of shares outstanding from *The Center for Research in Security Prices* (CRISP). The sample only includes earnings announcement data from calendar days and day t refers to the day of the announcement. Day t-1 refers to the last day when the market was open. For example, if an earning announcement occurs on a monday, t-1 refers to a friday. Day t-2 refers to two days prior to the day of the announcement and day t+1 refers to one day after the announcement when the market was last open. Furthermore, for the measure of market uncertainty, the variable VIX is used. VIX is *The Chicago Board Options Exchange Volatility Index,* which measures the expected 30-day volatility on the S&P 500.

Our data set includes 192,824 number of observations. We use a larger sample compared to HS (with 75,897 obs), incorporating both small and large US listed firms. We are interested in determining if the results from the original study (conducted using a sample from 1984-2013) remain when looking at a later time period as well as both small and large firms.

B) Summary Statistics

In this section we present the summary statistics for the most relevant variables in our study. All variables in *table 1* are explained in greater detail in the empirical framework section below.

Table 1 - Summary Statistics

A firm's own surprise is measured as ((EPS actual - EPS consensus)/Price(t-3)). The unexpected return for each observation is measured as the actual stock return minus the expected return of its reference portfolio, calculated by value weighting 125 portfolios based on market capitalization, book-to-market value, and momentum. The market cap is calculated three days before each firm's earning announcement day and scaled by dividing each company's market cap(t-3) with the yearly average market cap. The $Surprise_{t-1}$ is value-weighted by using each company's scaled market cap three days before the company's announcement.

Variable	Obs	Mean	SD	Min	Max
Surprise_t	192,824	-0.0145	0.3348	-9.9644	9.8181
Open Unexpected $\text{Return}_{(t,t+2)}$	192,824	1.52E-11	0.0937	-10.6714	0.7228
Close Unexpected $\text{Return}_{(t-2,t+1)}$	192,824	-0.0002	0.0911	-0.866	3.9825
Market cap_{t-3} (Millions of Dollars)	192,824	3,379	15,813	0.3938	935,561
Number of Analysts	192,824	4.2556	4.5202	1	43
Surprise_{t-1} Value Weighted	192,824	-0.0008	0.0024	-0.0075	0.0074

As can be seen in *table 1* above, firms' market capitalization in the sample stretch from circa 0.4 millions of dollars to circa 940,000 millions of dollars. This indicates a sample with a wider range of different market capitalization levels, compared to HS.

IV. Empirical Framework

A) Earnings Surprise Based on Analysts’ Consensus Estimates

The *Earnings surprise* is a key variable in our study. We follow the same procedure as in DellaVigna and Pollet (2009) and calculate each firm’s *earnings surprise* as the difference between a firm’s actual earnings and analysts’ consensus estimate, divided by the stock price three days before the announcement day. Analysts’ consensus estimates are calculated as an average of several analysts’ forecasts for company earnings. The forecasts are made between 2 and 15 days prior to the actual firm’s announcement day. A time window between 2 and 15 days prior to the announcement day follows the procedure in HS. They argue that the reason behind the given time window is to avoid outdated information while still obtaining a large sample of firms with analyst coverage.

A positive surprise corresponds to when a firm’s actual earnings exceed the analysts’ forecasted consensus. A negative earnings surprise occurs if the opposite is the case - if the analysts’ forecast is above the firm’s actual earnings.

The *earnings surprise* formula can be written as:

$$Surprise_{it} = \frac{Actual\ EPS_{it} - EPS\ Consensus_{i,[t-15,\ t-2]}}{Price_{i,\ t-3}} \tag{1}$$

Earnings surprises are calculated for US listed firms with announcement dates between the years 1990-2020. To reduce the influence of outliers, similarly to HS, observations in the 1st and 99th percentile for earnings surprises are excluded from the sample.

B) Value-weighted *Surprise* $_{t-1}$

Similarly to HS, we value-weight each observation using the market capitalization of each firm three days prior to the announcement day. The reason is that a firm's market capitalization is related to how much attention the firm receives. An earnings surprise for a large firm will get much more attention and be noticed by more investors. Thus, to capture that the earnings surprises for larger firms will have a more significant impact on the earnings surprises the next day, we value-weight earnings surprises with the market capitalization three days prior to the earnings announcement. We use the market capitalization three days prior to the announcement because that is in accordance with HS. Furthermore, it reduces the risk of the earning surprises having the time to affect the value of the market capitalization.

Further, as in HS, we scale market capitalization by the average in each year. The scaled market capitalization is calculated by dividing each firm's market capitalization with the yearly average market capitalization in the sample. As discussed in HS, the reason for using the scaled market capitalization is because the average market capitalization has increased over time and thus it is a way to avoid the risk of mechanically overweighting recent observations. Thus, unless otherwise stated, henceforth we value-weight each observation using each firm's market capitalization three days prior to the firm's announcement, scaled by the average market capitalization in that year.

The formula for calculating the value-weighted previous days' surprise can be written as:

$$Surprise_{t-1} = \frac{\sum_{i=1}^{N} (Mktcap_{i,\,t-4} * Surprise_{i,\,t-1})}{\sum_{i=1}^{N} Mktcap_{i,\,t-4}} \quad (2)$$

C) Unexpected Return

We use the same procedure as in HS to calculate return reactions. A return reaction is the difference between the actual return and the expected return, also known as the unexpected return. There are two return windows for the unexpected return, a shorter one using stock prices at market open and a longer one using stock prices at market close. The shorter return window is calculated from the day of the announcement until two days after the announcement, while the longer return window is calculated from two days prior to the announcement until one day after the announcement. A regression with a longer return window is advantageous because it includes the time period before each firm's announcement date. More specifically, HS explain that a longer return window decreases the risk that a negative relation between $Surprise_{t-1}$ and unexpected return can be explained by an overreaction to news on day t-1 and a subsequent correction when a firm's earnings are announced on day t.

In order to calculate the unexpected return, we first calculate the expected return. Similarly to HS, the expected return is calculated as the average return of a matched portfolio. The matched portfolio is calculated using a portfolio sorting technique in which common stocks from NYSE are grouped into 5 quintiles based on market capitalization, book-to-market value, and momentum. This procedure is similar to the portfolio sorting technique used in Daniel et al. (1997). The portfolio sorting results in a total of 125 (5x5x5) reference portfolios which, as in HS, are value-weighted by the average market capitalization of the stocks in each portfolio. Thereafter, all observations are matched with the one reference portfolio (out of the 125 portfolios) that they are a part of. Lastly, the unexpected return is calculated by subtracting the average return of the matched portfolio from the actual return.

The *Unexpected return* (UR) is calculated using the formula:

$$Unexpected\ Return\ =\ Actual\ Return\ -\ Average\ Portfolio\ Return$$

The theory of contrast effects predicts that firms' earning surprises the previous day will have a negative relation with the return reaction the following day. Given this information, we follow HS and estimate the following regression using stock prices at market open:

$$Unexpected\ Return_{i,\,[t,\,t+2]} = \beta_0 + \beta_1 Surprise_{t-1} + \varepsilon_{it} \qquad (3)$$

Standard errors are clustered by announcement date. All information contained in $Surprise_{t-1}$ is announced before the left-hand-side return measure begins. Thus, in an efficient market, β1 should equal zero. The contrast effects hypothesis, however, predicts that a high surprise yesterday makes any surprise today look slightly worse than it would appear if yesterday's surprise had been lower and vice versa. Thus, the theory of contrast effects predicts a negative coefficient on β1.

Notably, while regression (3) aims to test the contrast effects hypothesis, it is not the most direct test for contrast effects according to HS. In particular, HS explain that a negative β1 in regression (3) can be attributed to an alternative behavioral explanation whereby investors have mistaken expectations about what $Surprise_{t-1}$ implies for a firm announcing earnings the following day. For instance, investors may overinfer that a positive $Surprise_{t-1}$ is good news for a firm with an earnings announcement the following day t, leading to positive returns on day t-1 and then a negative return correction on day t when the firm's actual earnings are publicized. Thus, to avoid the results capturing this effect rather than the contrast effect, HS argues that a longer return window (t-2 to t+1) is to be preferred. Therefore, we follow HS and extend the return-window. Furthermore, as we extend the return window, similarly to HS, we use stock price data from market close instead of stock price data from market open.

We modify regression (3) into the following regression:

$$Unexpected\ Return_{i,\,[t-2,\,t+1]} = \beta_0 + \beta_1 Surprise_{t-1} + \varepsilon_{it} \qquad (4)$$

As discussed by HS, it is important to control for the earnings surprise associated with the firm's own earnings announcement as this will also influence the $Unexpected\ Return$. With this in mind, we flexibly control for all firm's own earnings surprises by adding several dummy variables *(Own Surprise Bins)*, one for each bin, to the regression, following the procedure used in HS. The *Own Surprise Bins* variable represents 20 equally sized bins, grouped in percentiles based on the size of each firm's earnings surprise. As described by HS, by using dummy variables for each bin, we nonparametrically allow each surprises' magnitude to be associated with a different level of unexpected return response. By implementing these changes (longer return window and the *Own Surprise Bins),* a negative $\beta 1$ is direct evidence of the contrast effect between the previous days' surprises and unexpected return *(HS, 2018)*.

When adding the dummy variable, *Own Surprise Bins,* to regression (3) and (4) we get the following new regressions:

$$UR_{i,\,[t,\,t+2]} = \beta_0 + \beta_1 Surprise_{t-1} + Own\,Surprise\,Bins + \varepsilon_{it} \qquad (5)$$

$$UR_{i,\,[t-2,\,t+1]} = \beta_0 + \beta_1 Surprise_{t-1} + Own\,Surprise\,Bins + \varepsilon_{it} \qquad (6)$$

D) The Return Reaction and Level of Market Uncertainty

This section is a direct replication of HS, however, we find it meaningful to test whether the results from our larger sample are influenced by the level of market uncertainty. At times, the stock market can be very volatile. For instance, during financial crises, when large and influential company news or scandals are released, during global crises, and surrounding initial public offerings. This can lead to high fluctuations in stock prices and cause a lot of uncertainty. Thus, we want to investigate if the theory of contrast effects still holds when controlling for market uncertainty. As in HS, we modify the baseline regression by including *The Chicago Board Options Exchange Volatility Index,* VIX, which measures the expected 30-day volatility on the S&P 500.

The regression can be written as:

$$UR_{i,\,[t-2,\,t+1]} = \beta_0 + \beta_1 Surprise_{t-1} + \beta_2 VIX_t + Own\,Surprise\,Bins + \varepsilon_{it} \quad (7)$$

In addition, and as tested in HS, another factor of interest is how previous days' earning surprises interact with market uncertainty and affect unexpected returns. To further investigate this interaction effect, regression (7) is modified by adding the variable $Surprise_{t-1}$*x VIX(t).* The coefficient of this independent variable shows the continuous interaction between previous days' surprises and VIX. Moreover, it captures the market uncertainty's influence on the relation between $Surprise_{t-1}$ and *Unexpected return*. The regression can be written as:

$$UR_{i,[t-2,t+1]} = \beta_0 + \beta_1 Surprise_{t-1} + \beta_2 VIX_t + \beta_3 Surprise_{t-1} * VIX_t + Own\,Surprise\,Bins + \varepsilon_{it} \quad (8)$$

Notice that regression (7) and (8) are direct replications of HS. However, HS study large firms and thus we follow the same procedure since we want to see how the level of market uncertainty influences the return reaction to firms' earnings surprises when looking at both large and small firms in the US financial market.

E) Other Potential Underlying Mechanisms

After testing contrast effects in relation to the level of market uncertainty, we were inspired to investigate if there are other underlying mechanisms affecting investors' perception of previous days' earnings surprises. Inspired by Conrad et al. (2002), we test the markets' strength in relation to contrast effects. Conrad et al. (2002) find that investors react differently to single-firm earnings announcements in good and bad times. This makes it relevant to test their findings in a contrast effect setting. Furthermore, researchers such as Kahneman and Tversky (1991) have found that humans are susceptible to loss aversion and that this psychological bias influences our behavior. In turn, Bouteska and Regaieg. (2020) specifically study loss aversion amongst investors. They find that investor loss aversion negatively impacts firm performance. Therefore, it is also of interest to test if loss aversion biases investors' reaction to previous days' earnings surprises.

i. The Relative Level of Market Strength

A potential mechanism underlying the return reaction to contrast effect is the relative level of market strength. Previous studies, namely Conrad et al. (2002), have shown that the stock market response to negative firm-specific earnings surprises increase as the relative level of the market rises. Thus, we modify our study to find out if the contrast effect in the financial market is affected by the level of market strength. More specifically, we want to see if each firm's earnings announcement occured in a high or low valuation state and determine if this is an underlying factor affecting the relation between $Surprise_{t-1}$ and *Unexpected return.*

As discussed by Conrad et al. (2002), due to the influence of inflation, the level of the market needs to be compared to some benchmark. In their study, they use future earnings as a benchmark for the level of prices and we chose to follow the same procedure. However, as pointed out by Conrad et al. (2002), there might still be a dilemma regarding if a strong market should be defined in absolute or relative terms. More specifically, if the absolute level of the P/E ratio or the difference between the current P/E ratio and the recent historical P/E ratio should be used to define the relative level of the market. Following Conrad et al. (2002), we choose the second alternative and measure the level of market strength using the variable DIFFPE. DIFFPE is calculated as the difference between each month's market P/E ratio and the average of the market's monthly P/E ratio over the previous 12 month period.

See the following formula:

$$DIFFPE = Monthly\ P/E(mkt)_t - Average\ yearly\ P/E(mkt)_t \qquad (9)$$

Where average market monthly P/E over the previous 12 months is calculated as:

$$P/E(mkt)_t = \frac{1}{\sum_{i=[1,Nt]} w_{it}(E_t(EPS_i)/P_{it}} \qquad (10)$$

The higher the value of DIFFPE, the stronger the market. Similarly, the lower the value of DIFFPE, the weaker the market.

We test DIFFPE in two ways. First, unlike Conrad et al. (2002), we begin by doing a similar test for DIFFPE as done for market uncertainty (VIX). More specifically, we are interested in determining if the return reaction to contrast effects in the financial market can be explained by the level of market strength. The market strength fluctuates and some periods are characterized by good times, while others as bad times. The market's strength is sensitive and it will quickly respond to shocks such as financial crises and significant disturbances. That said, we investigate if the relation between $Surprise_{t-1}$ and *Unexpected return* persists when accounting for the relative level of market strength. We modify our baseline regression by including the independent variable, DIFFPE.

The regression is modified into:

$$UR_{i,[t-2,t+1]} = \beta_0 + \beta_1 Surprise_{t-1} + \beta_2 DIFFPE_t + Own\ Surprise\ Bins + \varepsilon_{it} \qquad (11)$$

Another factor of interest is how the interaction between $Surprise_{t-1}$ and *Unexpected return,* changes as the level of market strength rises. To further investigate this interaction effect, the regression is modified by incorporating an interaction variable, $Surprise_{t-1} x\ DIFFPE_t$. This variable shows the continuous interaction between previous days' surprises and DIFFPE.

Moreover, the coefficient of the variable captures how much more $Surprise_{t-1}$affects *Unexpected return* for every unit that market strength rises.

The regression can be written as:

$$UR_{i,[t-2,t+1]} = \beta_0 + \beta_1 Surprise_{t-1} + \beta_2 DIFFPE_t + \beta_3 Surprise_{t-1} * DIFFPE_t + Own\ Surprise\ Bins + \varepsilon_{it} \quad (12)$$

Having conducted similar tests for DIFFPE as for VIX, we then proceed to test market strength similarly to Conrad et al. (2002). They group single earnings surprises based on DIFFPE and measure the reaction to good and bad earnings surprises in bad (low DIFFPE) and good times (high DIFFPE). While they study single-firm surprises, we perform the same test but using value-weighted $Surprise_{t-1}$to study contrast effects. We separate $Surprise_{t-1}$ into positive and negative surprises to test if the contrast effect varies in a strong or weak market. To do so, DIFFPE is sorted into five quintiles based on size where the lowest quintile represents a weak market and the highest quintile represents a strong market. The regressions below are run in a weak market (DIFFPE quintile = 1) and in a strong market (DIFFPE quintile = 5).

The following regressions are used:

$$UR_{i,[t-2,t+1]} = \beta_0 + \beta_1 PosSurprise_{t-1} + Own\ Surprise\ Bins + \varepsilon_{it} \quad (13)$$

$$UR_{i,[t-2,t+1]} = \beta_0 + \beta_1 NegSurprise_{t-1} + Own\ Surprise\ Bins + \varepsilon_{it} \quad (14)$$

ii. Investor Loss Aversion

To further investigate investor reactions, for example if some earnings news are more meaningful to investors than others, it is interesting to incorporate a discussion about decision-making theory. For example, do investors react more or less strongly when earnings news are worse or better than a reference point? A decision-making theory that is reference dependent is the theory of loss aversion, because for something to be deemed a loss or gain, it has to be relative to some benchmark. In our case, the reference point is the previous day’s earning surprise. Thus, if investors showcase asymmetric behaviour, specifically supposing that losses are more psychologically painful than gains, it could be explained by the theory of loss aversion. Loss aversion is an interesting theory, especially when it comes to financial decisions. The theory suggests that investors are less likely to buy stocks deemed risky, with a high chance of leading to a loss of money, even if the reward from such stocks could be very high. Thus, potential losses scare investors more than what potential gains are viewed as lucrative.

We test if the reactions to contrast effects are asymmetric and could be explained by investors being loss averse. Using the previous day's earnings surprise as a reference point, we categorize gains as when the value of a firms' own earning surprise is above the value of the previous day's surprise and losses as the reverse - when the value of a firm's own earning surprise is below the value of the previous day's earnings surprise. This entails that gains and losses are not defined as the actual surprise being positive or negative, rather they are defined by how they are perceived by investors in relation to the surprise the day before.

Loss aversion is tested using the following regressions:

$$UR_{i,[t-2,t+1]} = \beta_0 + \beta_1 Surprise_{t-1} + Own\ Surprise\ Bins + \varepsilon_{it} \quad when\ Surprise_t > Surprise_{t-1} \quad (15)$$

$$UR_{i,[t-2,t+1]} = \beta_0 + \beta_1 Surprise_{t-1} + Own\ Surprise\ Bins + \varepsilon_{it} \quad when\ Surprise_t < Surprise_{t-1} \quad (16)$$

F) Trading Strategy

The contrast effect theory predicts that today's earning news will appear slightly less impressive if yesterday's earnings surprise was positive and more impressive if yesterday's earning news were disappointing. This means that a positive $Surprise_{t-1}$will make firms with an announcement date the following day look less attractive, lowering investors' willingness to invest in those firms and result in decreased stock prices. While if $Surprise_{t-1}$ is instead negative, investors will find the earnings news of firms that announce the following day more impressive, leading to increased stock prices for those companies.

In an attempt to exploit these investor over- and underreactions, HS creates a trading strategy where one shorts (longs) companies that will announce the day following a positive (negative) $Surprise_{t-1}$. We follow the same logic and trading method. That is, we use the same long-short leg decision rule as HS to trade. However, thereafter the calculations are our own. Furthermore, since HS analyzes this trading strategy for large firms, it is interesting to test the strategy on our larger sample to see if these over-and unerreactions can be exploited when also incorporating smaller firms. Smaller firms tend to get less attention from investors. Thus, one could expect that when incorporating smaller firms, the payoffs from a trading strategy based on mispricings due to the contrast effects might be lower. However, using the same argument - that smaller firms get less attention - one could also hypothesize that while the arbitrage profits might be lower for small firms, they might be more long-lived due to the lack of attentiveness and subsequent lower competition amongst investors.

We assume no transaction costs and that we can borrow at the risk-free rate. Furthermore, we disregard dividends even if they affect stock prices, and thus could affect the results. The portfolios, consisting of firms that report earnings on the same day, will be held from t-1 to t+1. Using stock prices on market close, we start by calculating the daily return for every portfolio. Since a different number of companies report their earnings each day, we take this into consideration by calculating an *average portfolio return*(*t-1* to *t+1)* based on the number of earning announcements each day, using the formula:

$$Average\ Portfolio\ Return_{[t-1,\, t+1]} = \frac{\sum_{i=1}^{N} (Stock\ return_{it})}{Number\ of\ earning\ announcements_{t}} \tag{17}$$

We value-weight each trading portfolio, following the same approach as for value-weighted $Surprise_{t-1}$, using the scaled market cap(t-3) for all firms in each portfolio. This gives value-weighted portfolio returns for all trading portfolios between 1990-2020. The reason for value-weighting is because we want to account for the size of the firms in all trading portfolios.

See the following formula:

$$VW\ Portfolio\ Return_{[t-1,\, t+1]} = \frac{\sum_{i=1}^{N} (Mktcap_{i,\,[t-3]} *\ Average\ Portfolio\ Return_{[t-1,\, t+1]})}{\sum_{i=1}^{N} (Mktcap_{i,\,[t-3]}} \tag{18}$$

Then we convert the value-weighted portfolio returns into quarterly terms, giving us quarterly value-weighted portfolio returns. Lastly, we calculate the *total quarterly returns* each quarter between 1990-2020. The calculated portfolio returns are compared against the value-weighted S&P 500 market index, to see which yields higher returns.

III. Results

The following section includes the results from replicating HS but using later years and a larger sample, and the results from the extensions.

A) Baseline Results

Table 2 below shows the baseline results from the replication. The aim is to analyze if the return reaction to contrast effects persists in later years and when the sample size is increased to also incorporate smaller firms.

Table 2 - Baseline Results

This table shows the relation between unexpected return reactions and earning surprises of other firms that announced the previous day. The unexpected return is measured as the actual stock return minus the expected return of its reference portfolio, calculated by value weighting 125 portfolios based on market capitalization, book-to-market value, and momentum. Column (1) examines unexpected return from the market open on t to t+2 and column (2) examines unexpected return from the market close on t-2 to t+1. The $Surprise_{t-1}$ is value-weighted by using each company's scaled market capitalization three days before the company's announcement. The market capitalization is scaled by dividing each company's market cap(t-3) with the yearly average market cap. In both column (1) and (2), we flexibly control for firms' own earnings surprise by adding several dummy variables (*Own Surprise Bins*), one for each bin, to the regression. Standard errors are clustered by date and reported in parentheses. The confidence interval is 95%. *,** ,and *** indicate significance at the 10%, 5%, 1% levels, respectively.

	Open-to-Open Unexpected return [t, t+2]	Close-to-Close Unexpected return [t-2,t+1]
	(1)	(2)
$Surprise_{t-1}$ *VW mean*	-0.422**	-0.438*
	(0.201)	(0.256)
Own $surprise_{it}$ controls	Yes	Yes
adj. R-sq	0.008	0.018
Observations (N)	192,824	192,824

Standard errors in parentheses
*p< 0.1 **p< 0.05 ***p<0.01

Column (1), with a shorter return window and calculated using stock prices on market open day t to t+2, shows a significant β_1 of -0.422. Further, column (2), with a longer return window calculated using stock prices on market close from t-2 to t+1, also shows a significant β_1 of -0.438. Thus, column (2) shows a stronger negative relation between $Surprise_{t-1}$ and *Unexpected return* compared to column (1). The significant negative coefficients in the columns above, indicate that investors' reactions are biased from contrast effects in both small and large firms. Thus, the market is not efficient.

As in HS, we find a negative relation between the previous days' surprises and the corresponding return reaction to todays' surprises. Notably, our strongest relation (-0.438) is significantly weaker than HS's strongest relation (-0.924). However, this is reasonable because unlike them we incorporate several small firms which generally receive less attention from investors, thus the return reactions are likely less pronounced.

Following the procedure in HS, the results above are illustrated graphically, with $Surprise_{t-1}$ on the x-axis and *Unexpected return* on the y-axis.

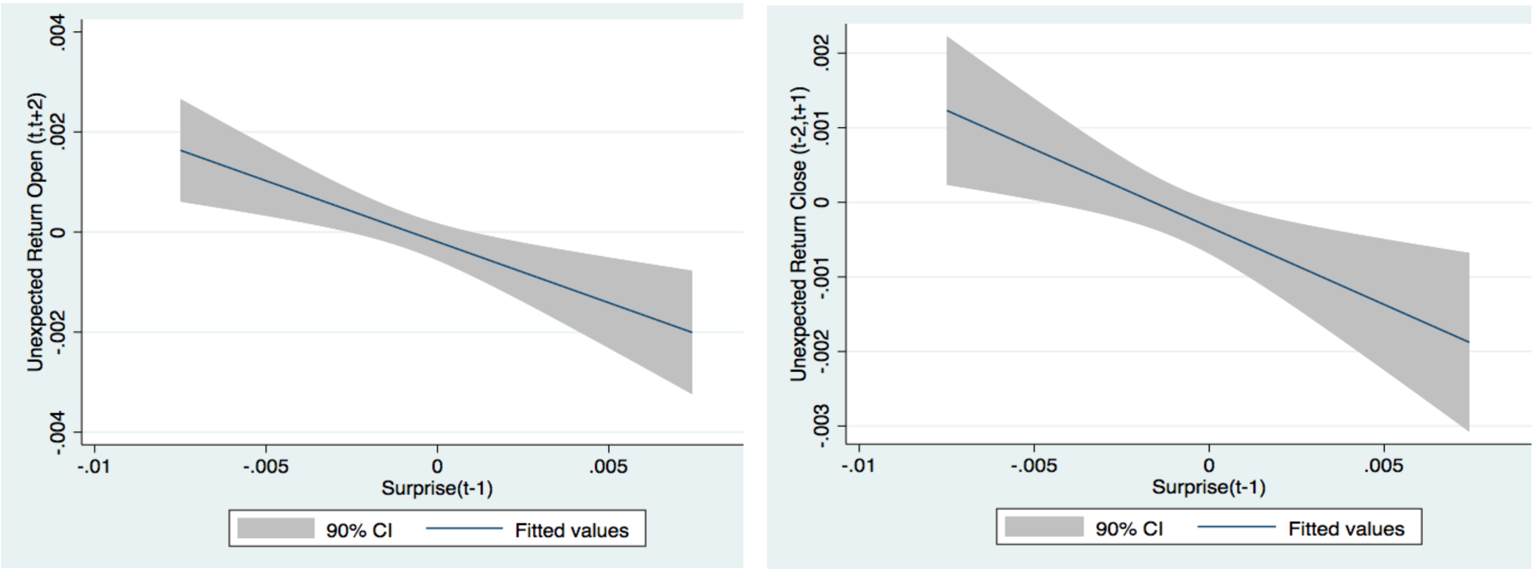


Figure 1. Unexpected Return Reaction to Surprise(t-1). The graphs illustrate the negative relation between unexpected return and previous days' surprises, for the two different return windows. The shorter return window, with stock prices on market open is illustrated in the left graph and the longer return window with stock prices on market close is illustrated in the right graph. The confidence interval is 90%.

The left sided graph in *Figure 1* shows a clear downsloping relation between the previous day's surprise and the unexpected return response. This indicates that today's earnings news will seem slightly less impressive, if yesterday's earnings surprises were positive and more impressive if yesterday's earnings news were disappointing.

The same graph, but with a longer return window, is illustrated to the right. This graph shows a steeper downsloping relation compared to the graph on the left. This could be because a longer return window better captures the contrast effects since it includes the time period before $Surprise_{t-1}$.

To summarize, both graphs indicate that there is a clear negative relation between previous days' earnings news and the return reaction to today's earnings news. This means that investor reactions continue to be biased by contrast effects when looking at later years and a wider range in firm size compared to HS.

B) Unexpected Return Reaction to Firms' Own Surprise

We want to see whether more positive and more negative earnings surprises on the previous day contribute differently to the return response to firms' own surprise. To do so, we replicate figure 3 in HS. The earnings surprises in the previous day ($Surprise_{t-1}$) are separated into deciles, where the blue line illustrates the highest decile and the red line the lowest decile. The result is depicted in *figure 2* below.

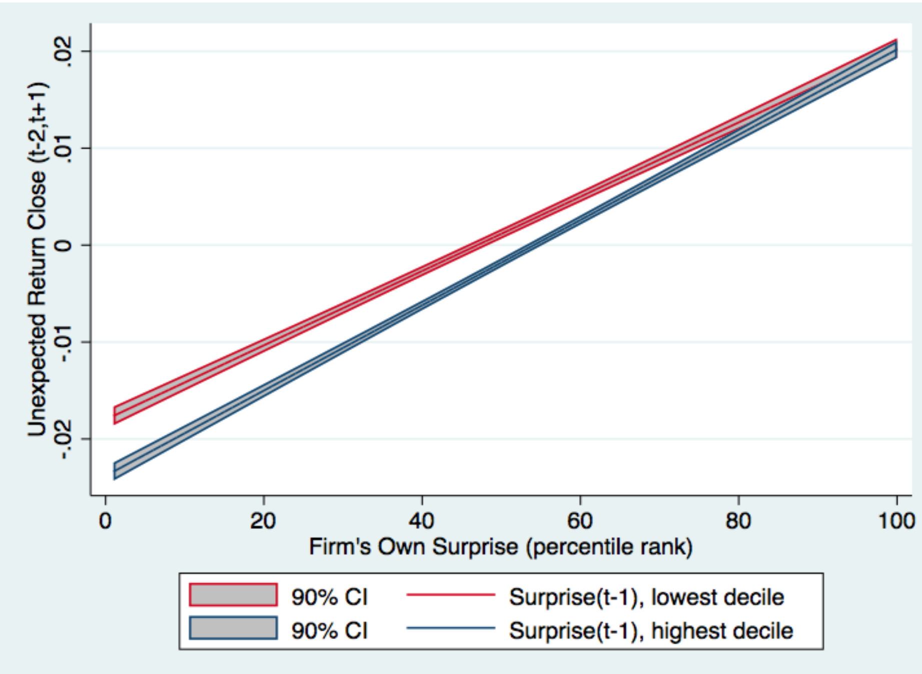


Figure 2. Unexpected Return Reaction to Firm's Own Surprise. This graph shows the unexpected return response to firms' own surprises day *t*, when the previous day's surprise is either in the highest or lowest decile, illustrated by the blue and red line respectively. The Firm's own surprise is calculated as ((EPS actual - EPS consensus)/Price(t-3)) and separated into hundred percentile ranks based on size. The unexpected return for each observation is measured as the actual stock return minus the expected return of its reference portfolio, calculated by value weighting 125 portfolios based on market capitalization, book-to-market value, and momentum. The confidence interval is 90%.

Figure 2 shows a clear upward sloping relation, for both the blue and the red line, between the return reaction and firms' own earnings surprises. Similarly to what HS finds, the return reaction is consistently higher for all values of firms' own surprises when the previous day's earnings surprise of other firms is in the lowest decile (red line) compared to when it is in the highest decile (blue line). This result indicates that investors react stronger to firms' own surprise when the previous days' earnings surprise is more negative compared to when it is more positive.

C) Market Uncertainty

The results from replicating HS and incorporating the variable VIX to measure the influence of market uncertainty can be seen in *table 3* below.

Table 3 - Market Uncertainty

This table displays whether the relation between surprises in the previous day and unexpected return can be explained by variations in market uncertainty (VIX). Column (1) displays regression 1 and column (2) displays regression 2. The variable $Surprise_{t-1}$ *x VIX(t)* shows the continuous interaction between previous days' surprises and VIX, capturing market uncertainty's influence on the relation between $Surprise_{t-1}$ and *Unexpected return*. Both regressions use close-to-close returns from t-2 to t+1. We flexibly control for firms' own earnings surprise using several dummy variables (*Own Surprise Bins*), one for each bin. Standard errors are clustered by date and in round parentheses. The regressions are carried out at a 95% confidence interval.*,** , and *** indicate significance at the 10%, 5%, 1% levels, respectively.

	Close-to-Close Unexpected return [t-2, t+1] (1)	(2)
Surprise$_{t-1}$	-0.439*	-2.011
	(0.268)	(1.377)
VIX	-8.31E-07	0.0002
	(0.0002)	(0.0002)
Surprise$_{t-1}$ x VIX		0.081
		(0.078)
Own Surprise$_{it}$ controls	Yes	Yes
R^2	0.018	0.019
Observations	192,792	192,792

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

Column (1) shows that $Surprise_{t-1}$ still has a significant negative relation with *Unexpected return* after controlling for VIX. This indicates that the result is not significantly influenced by variations in market uncertainty.

Column (2), when including the interaction variable $Surprise_{t-1}$ *x VIX,* shows how the relation between $Surprise_{t-1}$ and *Unexpected return* changes as the level of VIX rises. The non-interaction coefficient (-2.011) explains how much $Surprise_{t-1}$ effects returns when VIX is zero while the interaction coefficient (0.081) explains how much more $Surprise_{t-1}$ effects returns as VIX rises. Notably, the relation between $Surprise_{t-1}$ and *Unexpected return* remains negative when incorporating the interaction variable.

D) Underlying Mechanisms

This section shows the results from testing potential mechanisms underlying the contrast effect. More specifically, if investors react differently to contrast effects under varying market strengths and due to psychological biases, namely loss aversion.

i. The Relative Level of Market Strength

This section includes the results from measuring the influence of market strength on the return reaction to contrast effects.

The results from modifying the regression by adding a variable for market strength, DIFFPE as well as an interaction variable, $Surprise_{t-1}$ *x DIFFPE,* can be seen in *table 4* below.

Table 4 - The Relative Level of Market Strength

This table displays whether the relation between surprises in the previous day and *Unexpected return* can be explained by variations in the relative level of the market (market strength), measured by incorporating the variable *DIFFPE*. *DIFFPE* is calculated as the difference between each month's market P/E ratio and the average of the market's monthly P/E ratio over the previous 12 months' period. In regression 2, we add the interaction variable $Surprise_{t-1}$ *x DIFFPE*, which shows the continuous interaction between previous days surprises and DIFFPE. The *returns* are calculated, using close stock price data from t-2 to t+1. We flexibly control for firms' own earnings surprise using several dummy variables (*Own Surprise Bins*), one for each bin. Standard errors are clustered by date and in round parentheses. The confidence interval is 95%.*,** , and *** indicate significance at the 10%, 5%, 1% levels, respectively.

	Close-to-Close Unexpected return [t-2, t+1] (1)	(2)
$Surprise_{t-1}$	-0.433*	-0.410
	(0.256)	(0.254)
DIFFPE	-8.43E-06	-8.90E-07
	(0.00001)	(0.00001)
$Surprise_{t-1}$ x DIFFPE		0.007
		(0.005)
Own $Surprise_{it}$ controls	Yes	Yes
R^2	0.018	0.018
Observations	192,824	192,824

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

As shown in *table 4* column (1), $Surprise_{t-1}$ still has a significant negative relation with *Unexpected return* after controlling for DIFFPE.

Column (2) shows how the relation between $Surprise_{t-1}$ and *Unexpected return* changes as the market strength rises. The non-interaction coefficient shows that $Surprise_{t-1}$ still has a negative relation with *Unexpected return* after implementing the interaction variable $Surprise_{t-1}$ *x DIFFPE*. Moreover, the coefficient of the interaction variable explains how much more $Surprise_{t-1}$ effects returns as DIFFPE rises from zero. Notably, it is not significantly different from zero.

Conrad et al. (2002) find that the return reaction to negative single-firm earnings surprises increases with market strength while positive single-firm earnings surprises decrease as market strength increases. The results from testing these findings in a contrast-effect setting can be found in *table 5* below.

Table 5 - Positive and Negative Surprises Relative Market Strength

This table shows the relation between $Surprise_{t-1}$ and *Unexpected return*, when the previous days' surprise is divided into positive and negative and the market is defined as either weak or strong. Column (1) and (2) illustrate the results when $Surprise_{t-1}$ is positive and column (3) and (4) when $Surprise_{t-1}$ is negative. Column (1) and (3) indicate a weak market (DIFFPE quintile = 1) and column (2) and (4) a strong market (DIFFPE quintile = 5). All columns include *own surprise controls* which are 20 equally sized bins, grouped based on own earning surprises, plus a dummy for zero earning surprises. The *Unexpected returns* are calculated, using close stock price data from t-2 to t+1. We flexibly control for firms' own earnings surprise using several dummy variables (*Own Surprise Bins*), one for each bin. Standard errors are clustered by date and in round parentheses. The confidence interval is 95%.*,** , and *** indicate significance at the 10%, 5%, 1% levels, respectively.

	Positive $Surprise_{t-1}$		Negative $Surprise_{t-1}$	
	Weak market	Strong market	Weak market	Strong market
Unexpected return$_{(t-2,t+1)}$	-1.289	-0.118	-0.457	-1.428**
Own Surpriseit Controls	Yes	Yes	Yes	Yes
R^2	0.025	0.028	0.012	0.016
Observations	5,431	13,491	33,238	29,358

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

In *table 5* column (1) and (2), when looking at positive surprises the day before, we find a stronger relation between $Surprise_{t-1}$ and *Unexpected return* when the market is weak compared to when it is strong. Evidently, when earnings surprises the day before are positive, the return reaction to contrast effect decreases as the market strength increases.

Column (3) and (4) include the results for negative earnings surprises the day before. We find that the relation between $Surprise_{t-1}$ and *Unexpected return* is more negative when the market is strong compared to when it is weak. In other words, when $Surprise_{t-1}$ is negative, the return reaction to contrast effect increases as the market strength increases.

ii. Investor Loss Aversion

This section includes the results from our investigation whether the varying return reaction to previous days' earnings surprises could be explained by investors being loss averse. Since the theory of loss aversion is reference dependent, we test if investors use the previous days' earnings surprises as a reference point. This means that a gain is when the value of a firms' own earnings surprise is above the value of the previous days' surprises and a loss is when the value of a firm's own earnings surprise is below the previous days' earnings surprises.

Table 6 - Investor Loss Aversion in Relation to Contrast Effects

This table shows how varying return reactions to previous days' surprises could be explained by investors being loss averse. We use the $Surprise_{t-1}$ for every observation as a reference point. $Surprise_t > Surprise_{t-1}$ refers to a gain and $Surprise_t < Surprise_{t-1}$ refers to a loss. Column (1) shows the relation between previous days' earning surprises and returns for gains and column (2) shows the relation between previous days' earning surprises and returns for losses. We flexibly control for firms' own earnings surprise using several dummy variables (*Own Surprise Bins*), one for each bin. Standard errors are reported in parentheses and clustered by date. The confidence interval is 95%. *,** , and *** indicate significance at the 10%, 5%, 1% levels, respectively.

	Close-to-Close Unexpected return [t-2, t+1]	
	$Surprise_t > Surprise_{t-1}$	$Surprise_t < Surprise_{t-1}$
$Surprise_{t-1}$	-0.205 (0.314)	-0.676** (0.310)
Own $Surprise_{it}$ Controls	Yes	Yes
adj. R-sq	0.013	0.005
Observations (N)	100,891	91,933

Standard errors in parentheses
*p< 0.1 **p<0.05 ***p< 0.01

Column (1) illustrates the return reaction to previous days' surprises when investors experience a gain. Notably, the results are weakly significant apart from zero and the relation is less negative compared to the baseline results found in *table 2.*

Column (2) illustrates the return reaction to previous days' surprises when investors experience a loss. The results show a negative significant relation. Moreover, the negative relation between $Surprise_{t-1}$ and *Unexpected return* is stronger compared to the baseline results found in *table 2*.

The results of column (1) and (2) indicate that when investors experience a loss, the return reaction is stronger to previous days' surprise, compared to when they experience a gain.

E) Trading Strategy

The evidence of contrast effects from our results make it possible to predict investor reactions on day *t* by analyzing firms' earning surprises that were announced in the previous day. Similarly to HS, we construct trading portfolios based on the previous days' earnings surprise to see if one can take advantage of investors' over-and underreactions from the contrast effect. The results from the short-term trading strategies, held from day t-1 to t+1, can be found below.

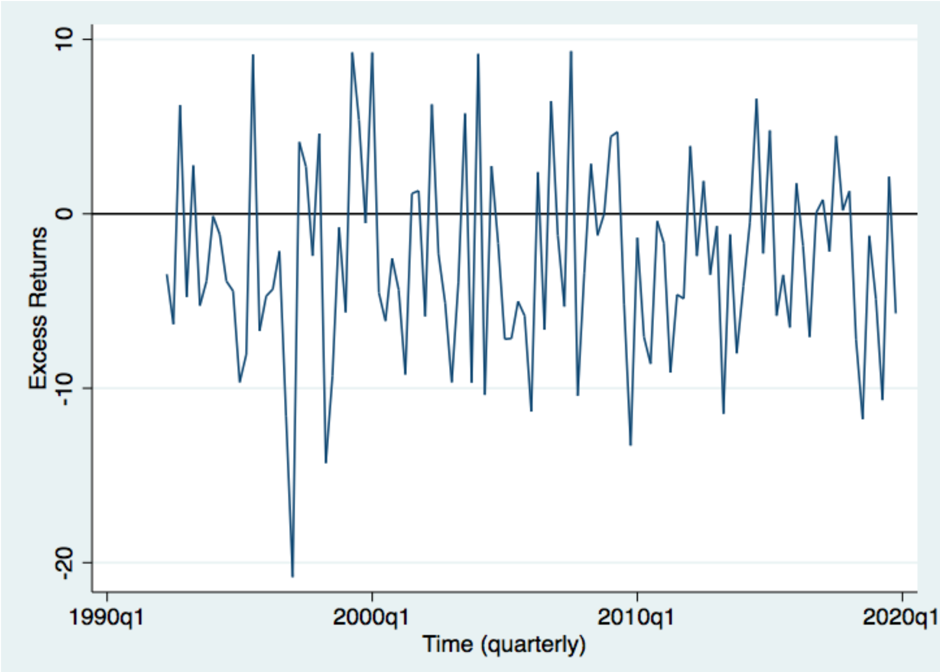


Figure 3. Quarterly Long-Short Portfolio Excess Return. The figure illustrates the portfolio excess return from the long-short portfolio trading strategy. That is, the difference between the total quarterly return from the long-short trading portfolio which incorporates the effects of the contrast effect and the market return (S&P 500 Index).

Total quarterly excess returns are measured as the difference between the total quarterly returns of the trading portfolios and the S&P 500 index (market portfolio). The graph indicates that the total excess returns are very volatile 1990-2020.

Further, to look at the excess return on a yearly basis, we calculate annualized returns each year between 1990-2020 and compare against the market index. These results can be found in *figure 4* below.

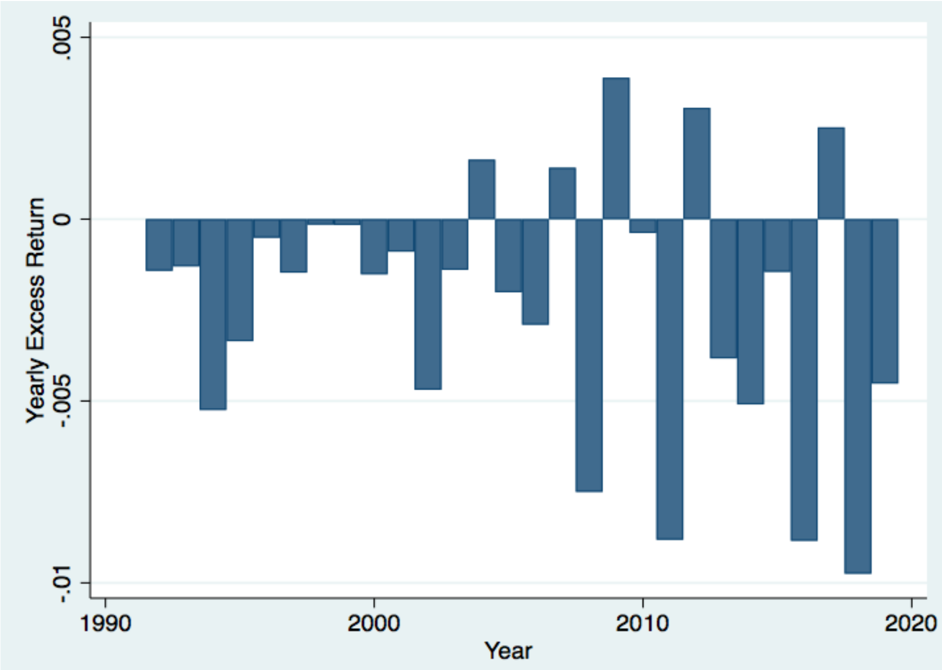


Figure 4. Annual Long-Short Portfolio Excess Return. The figure illustrates the annual excess return, calculated as the difference between the annualized return for the constructed long-short trading portfolio and S&P 500 index between 1990-2020.

Figure 4 shows that the long-short trading portfolio only yields higher annualized returns in five years between 1990-2019. This indicates that it is more profitable to invest in the market (S&P500) than in the contrast-effect trading portfolio.

i. Long Trading Portfolio Strategy

Having found that the market portfolio outperforms the long-short trading strategy, we test only the long-leg of the contrast-effect trading strategy to see if it can outperform the market. We know from previous tests (illustrated in *figure 2*) that investors' return response to firms' own surprise on day t is higher when the earnings surprise the previous day is more negative compared to when it is more positive. This result speaks to only testing the long-leg of the contrast-effect trading strategy because it should perform better than the combined long-short leg strategy. To test this, we go long firms that will announce the following day if $Surprise_{t-1} < 0$ and instead of going short when $Surprise_{t-1} < 0$, we invest in the market.

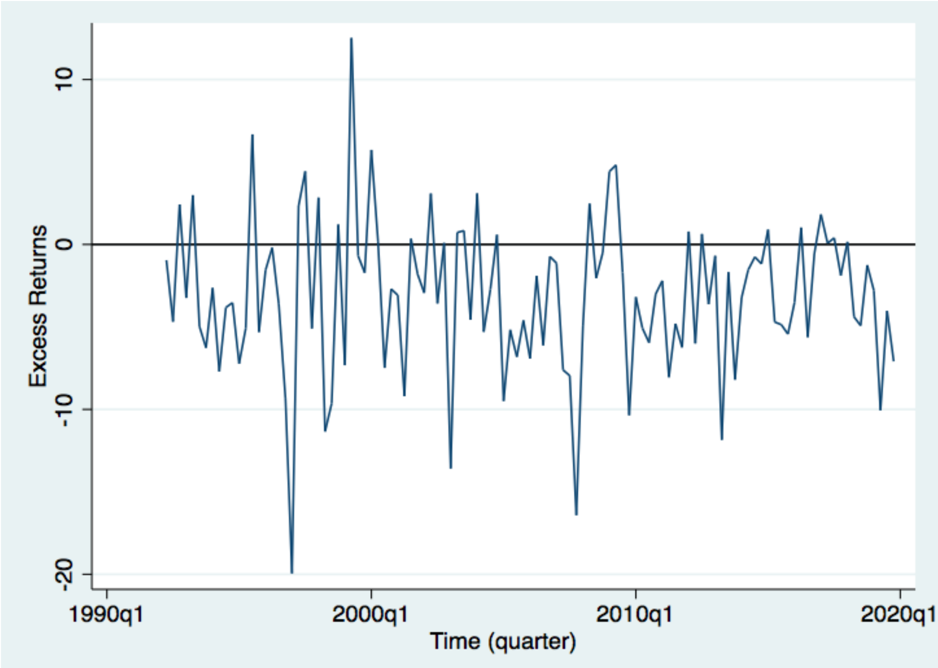


Figure 5. Quarterly Long Portfolio Excess Return. The figure illustrates quarterly excess return from the long portfolio trading strategy. That is, the difference between the long trading portfolio and the market portfolio (S&P 500 Index) between 1990-2020.

From *figure 5* above, it is evident that there are high-points where the long-leg strategy beats the market, however, there are also several low-points where the strategy underpreforms the market.

The quarterly returns are converted into annualized returns to get the results on a yearly basis. We compare the annualized long-leg portfolio returns with the market to see which yields higher returns.

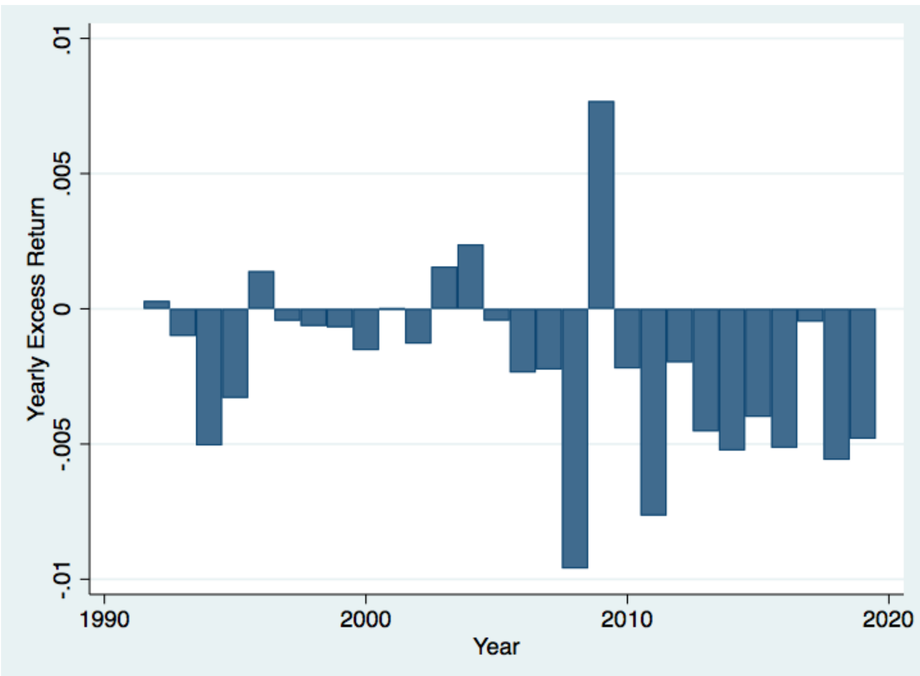


Figure 6. Annual Long Portfolio Excess Return. This table illustrates the annual excess return for the long portfolio strategy from 1990 to the end of 2020. The yearly excess return is calculated as the difference between the annualized yearly return for the long portfolio and the S&P 500 index.

Figure 6 above shows that the long-leg trading portfolio strategy yields higher returns in seven years between 1990-2020. Thus, the market tends to outperform the long-leg trading portfolio and it appears to be more profitable to invest in the market.

To summarize the trading-strategy results, given our previously stated assumptions, we find that the market generally outperforms both contrast-effect trading strategies. Furthermore, we do not find a significant difference in the performance of the long-short and long-leg contrast-effect trading strategies.

V. Limitations

The study contains some limitations. First, the use of VIX to measure market uncertainty can be discussed. VIX measures short-term market volatility in option prices on various exchanges. In our case, we chose VIX for the S&P 500. Since we study both large and small firms, some of the companies in our dataset are not included in the S&P 500 index and thus we lost a few smaller companies when incorporating the VIX measure. As a result, one could argue whether VIX is an appropriate approximation for the level of the market uncertainty for all the companies in our sample.

Second, the use of $Surprise_{t-1}$ as the reference point in our loss aversion test might not be the best representation of reality. $Surprise_{t-1}$ is calculated as a value-weighted average of several companies' own firm surprises that announce the same day. However, investors might not use the value-weighted sum of the surprises the day before as their reference point but rather the surprise of the largest firm the day before. Therefore, only using the largest firm as the reference point for gains and losses might be to prefer.

Lastly, as mentioned in HS, another concern with regards to the analysts is that they are susceptible to different biases. For instance, if analysts are biased or generally uninformed when making their forecasts, the consensus estimate might not be a true reflection of reality. This creates a snowball effect in which there might appear to be earnings surprises when in fact these are simply created due to biases or misinformation. Misleading earnings surprises in turn affect the return reaction due to contrast effects and can create the illusion that such an effect exists when in reality, it might not. This is very difficult to investigate and thus something we cannot rule out nor incorporate into our calculations.

VI. Conclusion

In this paper, we study underlying mechanisms affecting investor reactions to contrast effects in the US financial market. To begin, we follow the same procedure as HS, however, studying later years (1990-2020) as well as both large and small firms to confirm that contrast effects in the financial market persist. Thereafter, we extend their study and include new parameters, namely market strength and loss aversion. The aim is to explore if these potential underlying mechanisms influence investors' reactions to contrast effects.

The baseline results from the replication of HS, studying a later time period and a larger sample of firms, confirms that investors' perceptions are biased from previous days' news. This concludes that contrast effects result in market over- and underreactions that are reflected in mispricings in the stock market. Furthermore, when continuing the replication by separating the earning surprises the day before into more positive and more negative surprises, we also confirm the results in HS (see *figure 2* above). That is, in accordance with the contrast effect hypothesis, the return response to a given earnings surprise today is higher when yesterday's news was bad compared to when yesterday's news were good.

In terms of our extensions, when studying market strength as an underlying mechanism to contrast effects, we can conclude that investor behavior differs depending on market strength and if the earnings surprise the day before was positive or negative. More specifically, investors appear to be most susceptible to contrast effects in a strong market when the earnings surprise the day before was negative. Having studied external factors that could influence investor behavior, we proceed to look at internal processes, namely psychological biases. We find that the return response to earnings surprises is of higher magnitude when investors experience a loss compared to when they experience a gain. This result shows that investor behavior is asymmetric and thus the varying return reaction to contrast effects could be explained by investors being loss averse.

Since we find that investors' decisions are influenced by news from the previous day, it was of interest to study if these mispricings could be exploited in any way. Similar to HS, we construct a long-short trading strategy, however, we also include smaller firms. Different from HS, we also create a single long-leg trading strategy. Both trading strategies aim to take advantage of mispricings from the contrast effect. Interestingly, unlike HS, we find that both trading portfolios generally underperform the market. It is relevant to analyze what might have contributed to this surprising result. One possible explanation is that our sample contains more smaller firms than HS. Many of these small firms only have one analyst forecast, indicating that they receive less attention from analysts and therefore likely from investors as well. HS even confirms, in their study, that contrast effects are strongest for firms covered by two or more analysts. Thus, it is logical to assume that since smaller firms receive less coverage, the arbitrage opportunities will be smaller, making them more difficult to exploit in a profitable trading strategy.

VII. Discussion

Firm earning surprises have been studied in various settings before. Ball and Brown (1968) were among the first to study single firm earning announcements. Later on, HS analyzed earning surprises in a new setting, namely in relation to contrast effects. We extend the study by HS and inspired by several other researches such as Conrad et al. (2002), we investigate potential underlying mechanisms affecting return reactions to contrast effects. When incorporating the relative level of market strength into our study, we find evidence that investors' reactions to contrast effects are linked to the prevailing stock market state. Macroeconomic factors, such as interest rates and inflation, largely influence the stock market state. Evidence of this is now during the ongoing pandemic, where monetary policy in the form of quantitative easing has resulted in a stronger stock market than usual during the first and thus far in the second quarter of 2021 (*Monetary Policy Report, Riksbanken*). That said, it would be no surprise if the return reaction to contrast effects is also influenced by macroeconomic factors. However, studying contrast effects in relation to macroeconomic factors would be an entirely new study in itself. For instance, an interesting alternative study for the future would be to analyze the relation between monetary policy and investor's reaction to contrast effects.

From studying contrast effects in the financial market and in relation to psychological biases, we find that it can be critical to incorporate a discussion on human behavior in order to be able to interpret results. We learn that investors are not only biased from previous days' earnings announcement in absolute terms, but also in relative terms. This is consistent with prospect theory discussed earlier in the text, which states that individuals classify outcomes as gains and losses relative to a reference point. Moreover, when closely examining these results, we also learn that investors' reactions to contrasts differ in magnitude depending on if the contrast makes earnings appear better or worse. More specifically, we find that investors react more negatively to bad news, compared to how they react positively to good news and conclude that this could be evidence of loss aversion. This inconsistent behavior - that return reactions are stronger for losses compared to gains - is in turn reflected in the stock market and leads to asymmetric mispricings from earning news. If investors learn more about human asymmetric behaviors such as these, they could find and exploit new arbitrage opportunities that they were previously unaware of.

While on the subject of loss aversion, we are aware that concluding that our results could be driven by investors being loss averse might be a simplification of reality. What defines a gain and what defines a loss is subjective. In our case, a loss is when today's surprise is lower than the previous day's surprise, while a gain is when the opposite occurs. This definition relies on the relative relation between the previous days' surprise and today's surprise. However, one could question whether the use of a reference point to define gains and losses is in accordance with loss aversion theory. According to Khaneman and Tversky who emphasize reference points in relation to loss aversion, it probably is. In fact, they criticize standard models of decision making because they assume that preferences - which are largely determined by reference points - do not depend on one's current state or current assets (*Khaneman & Tversky, 1991)*. Moreover, in their discussion of loss aversion, Khaneman and Tversky explain that the central assumption of the theory is that losses and disadvantages have a larger impact on preferences than gains and advantages (*Khaneman & Tversky, 1991*). According to this formulation, a $Surprise_t$ value below $Surprise_{t-1}$would arguably classify as a disadvantage if not as a loss and the reverse - a $Surprise_t$ above $Surprise_{t-1}$- as an advantage, if not as a gain. This entails that loss aversion is a broader theory than simply focusing on whether value in absolute terms is lost or gained. In other words, losses and gains can also be measured in relative terms.

After studying market conditions and human behavior in relation to the financial market, we can conclude that both are underlying mechanisms affecting investors' reactions to contrast effects. However, there are still several unknowns. For instance, there could be other underlying factors that are difficult to detect and that can have affected the outcome of the results. Because of this, in future studies, it would be interesting to test other market conditions and behavioral biases and their relation to contrast effects. Doing so could provide new insightful findings as to what factors underlie investors' reaction to contrast effects.

VII. References

Amos Tversky, and Daniel Kahneman. “Loss Aversion in Riskless Choice: A Reference-Dependent Model.” *The Quarterly journal of economics* 106.4 (1991): 1039–1061. Web.

Bouteska, A. and Regaieg, B. (2020), "Loss aversion, overconfidence of investors and their impact on market performance evidence from the US stock markets", *Journal of Economics, Finance and Administrative Science*, Vol. 25 No. 50, pp. 451-478.

Deshpande, Shreesh, and Marko Svetina. “Negative Earnings Surprises: When Is the Glass Half-Full?” *Managerial finance 40.8* (2014): 804–820. Web.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56. doi:10.1016/0304-405X(93)90023-5

Hartzmark, S. M., & Shue, K. (2018). A tough act to follow: Contrast effects in financial markets. *Journal of Finance, 73*(4), 1567-1613. doi:10.1111/jofi.12685

Hou, Kewei, Lin Peng, and Wei Xiong. 2006. A tail of two anomalies: The implications of investor attention for price and earnings momentum. Working Paper, Ohio State University.

Jennifer Conrad, Bradford Cornell, and Wayne R. Landsman. “When Is Bad News Really Bad News?” *The Journal of finance (New York)* 57.6 (2002): 2507–2532. Web.

Kent Daniel et al. “Measuring Mutual Fund Performance with Characteristic-Based Benchmarks.” *The Journal of finance (New York)* 52.3 (1997): 1035–1058. Web.

Köszegi, Botond, and Matthew Rabin. “A Model of Reference-Dependent Preferences.” *The Quarterly journal of economics* 121.4 (2006): 1133–1165. Web.

Nichols, D. Craig, and James M Wahlen. “How Do Earnings Numbers Relate to Stock Returns? A Review of Classic Accounting Research with Updated Evidence.” *Accounting horizons* 18.4 (2004): 263–286. Web.

Ray Ball, and Lakshmanan Shivakumar. “How Much New Information Is There in Earnings?” *Journal of accounting research* 46.5 (2008): 975–1016. Web.

Ray Ball, and Philip Brown. “An Empirical Evaluation of Accounting Income Numbers.” *Journal of accounting research* 6.2 (1968): 159–178. Web.)

Rodríguez, Gabriel, and Sara Blanco. “Contrast Effect on the Perception of the Severity of a Criminal Offence.” *Anuario de psicología jurídica (Madrid, España)*26.1 (2016): 107–113. Web.

Stefano DellaVigna, and Joshua M. Pollet. “Investor Inattention and Friday Earnings Announcements.” *The Journal of finance (New York)* 64.2 (2009): 709–749. Web.

Sveriges Riksbank. “Monetary Policy Report, April 2021”. *Sveriges Riksbank.* (2021): Web. www.riksbank.se

Yeates, Peter et al. “Relatively Speaking: Contrast Effects Influence Assessors’ Scores and Narrative Feedback.” *Medical education* 49.9 (2015): 909–919. Web.

VII. Appendix

Table 1 - Summary Statistics

Variable	Obs	Mean	SD	Min	Max
Surprise$_t$	192,824	-0.0145	0.3348	-9.9644	9.8181
Open Unexpected Return$_{(t,t+2)}$	192,824	1.52E-11	0.0937	-10.6714	0.7228
Close Unexpected Return$_{(t-2,t+1)}$	192,824	-0.0002	0.0911	-0.866	3.9825
Market cap$_{t-3}$ (Millions of Dollars)	192,824	3,379	15,813	0.3938	935,561
Number of Analysts	192,824	4.2556	4.5202	1	43
Surprise$_{t-1}$ Value Weighted	192,824	-0.0008	0.0024	-0.0075	0.0074

Table 2 - Baseline Results

	Open-to-Open Unexpected return [t, t+2]	Close-to-Close Unexpected return [t-2,t+1]
	(1)	(2)
$Surprise_{t-1}VW\ mean$	-0.422**	-0.438*
	(0.201)	(0.256)
Own *surprise$_{it}$* controls	Yes	Yes
adj. R-sq	0.008	0.018
Observations (N)	192,824	192,824

Standard errors in parentheses
*p< 0.1 **p< 0.05 ***p<0.01

Figure 1 - Unexpected Return Reaction to Surprise(t-1)

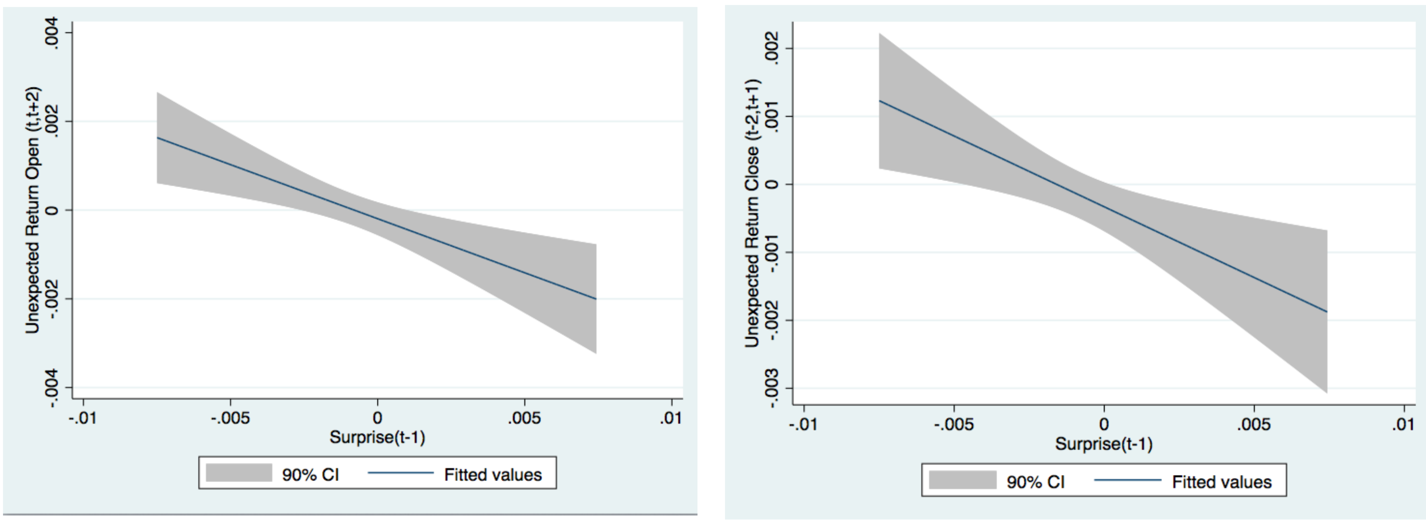


Figure 2 - Unexpected Return Reaction to Firm's Own Surprise

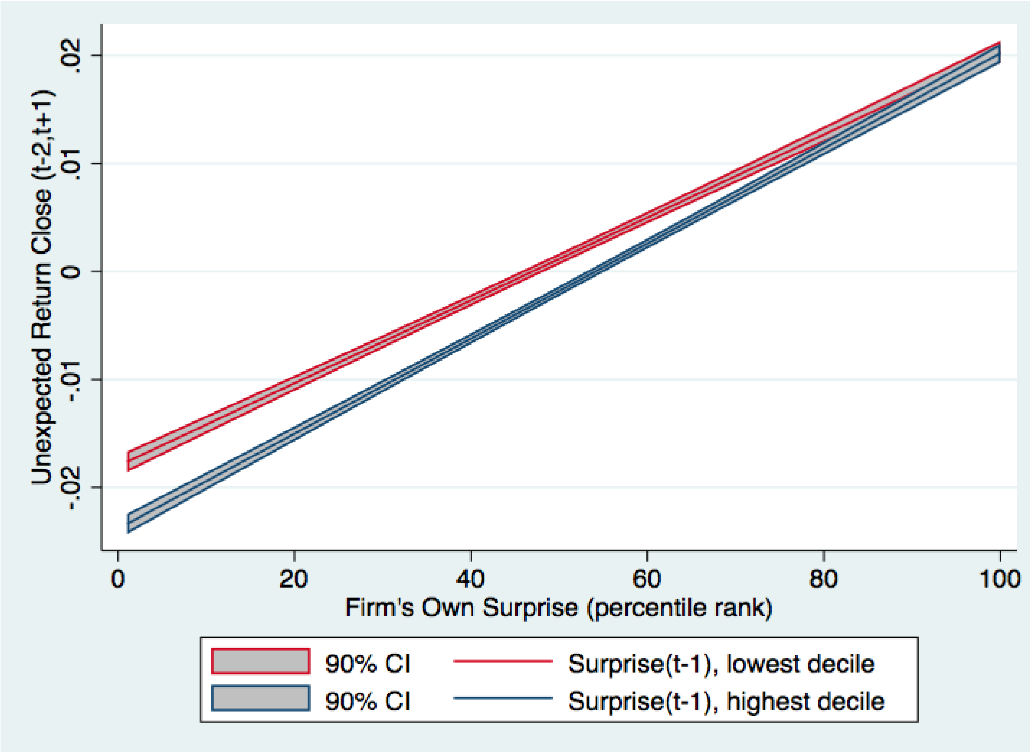


Table 3 - Market Uncertainty

	Close-to-Close Unexpected return [t-2, t+1] (1)	(2)
Surprise$_{t-1}$	-0.439*	-2.011
	(0.268)	(1.377)
VIX	-8.31E-07	0.0002
	(0.0002)	(0.0002)
Surprise$_{t-1}$ x VIX		0.081
		(0.078)
Own Surprise$_{it}$ controls	Yes	Yes
R^2	0.018	0.019
Observations	192,792	192,792

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

Table 4 - The Relative Level of Market Strength

	Close-to-Close Unexpected return [t-2, t+1] (1)	(2)
$Surprise_{t-1}$	-0.433*	-0.410
	(0.256)	(0.254)
DIFFPE	-8.43E-06	-8.90E-07
	(0.00001)	(0.00001)
$Surprise_{t-1}$ x DIFFPE		0.007
		(0.005)
Own $Surprise_{it}$ controls	Yes	Yes
R^2	0.018	0.018
Observations	192,824	192,824

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

Table 5 - Positive and Negative Surprises Relative Market Strength

	Positive $Surprise_{t-1}$		Negative $Surprise_{t-1}$	
	Weak market	Strong market	Weak market	Strong market
Unexpected $return_{(t-2,t+1)}$	-1.289	-0.118	-0.457	-1.428**
Own Surpriseit Controls	Yes	Yes	Yes	Yes
R^2	0.025	0.028	0.012	0.016
Observations	5,431	13,491	33,238	29,358

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

Table 6 - Investor Loss Aversion in Relation to Contrast Effects

	Close-to-Close Unexpected return [t-2, t+1]	
	$Surprise_t > Surprise_{t-1}$	$Surprise_t < Surprise_{t-1}$
$Surprise_{t-1}$	-0.205 (0.314)	-0.676** (0.310)
Own $Surprise_{it}$ Controls	Yes	Yes
adj. R-sq	0.013	0.005
Observations (N)	100,891	91,933

Standard errors in parentheses
*p< 0.1 **p<0.05 ***p< 0.01

Figure 3 - Quarterly Long-Short Portfolio Excess Return

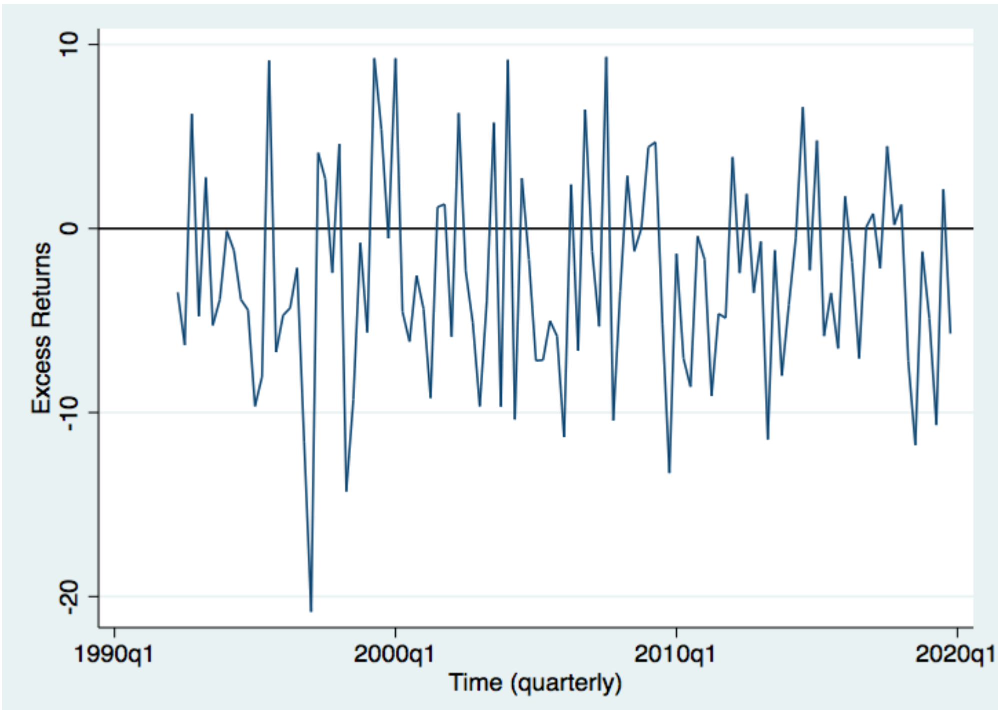


Figure 4 - Annual Long-Short Portfolio Excess Return

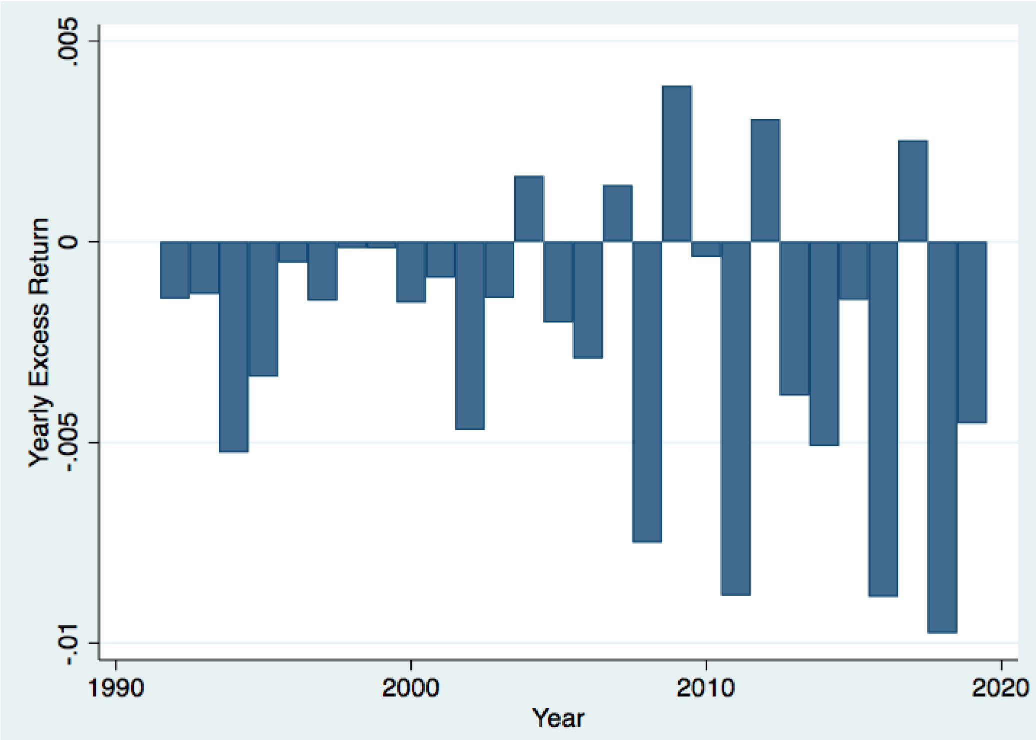


Figure 5 - Quarterly Long Portfolio Excess Return

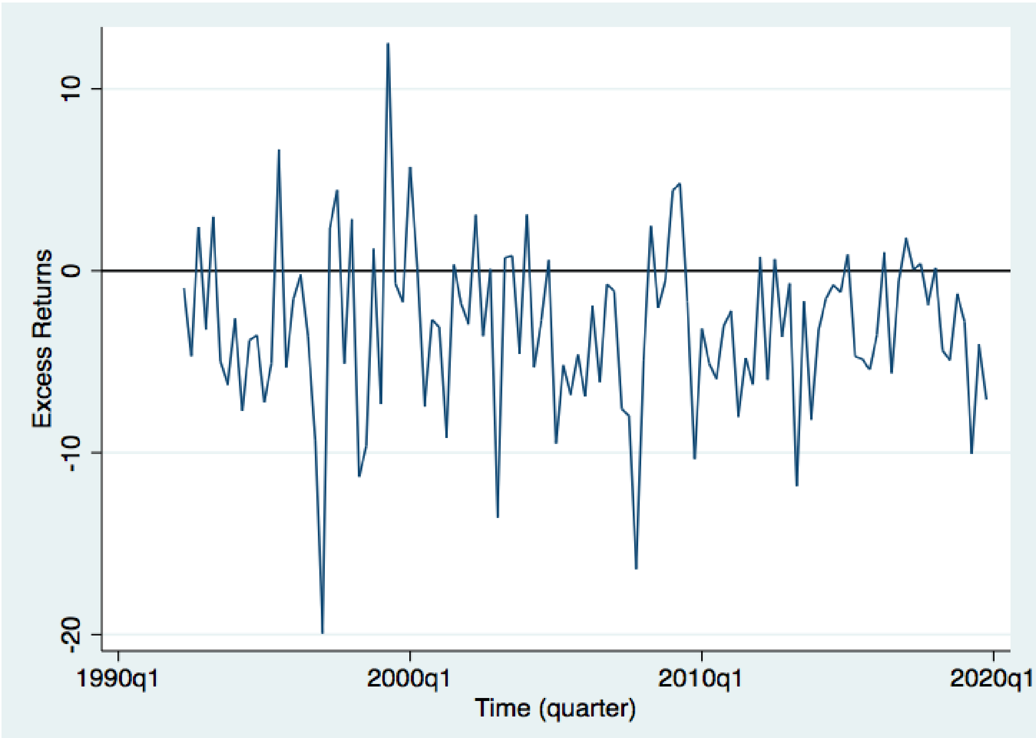
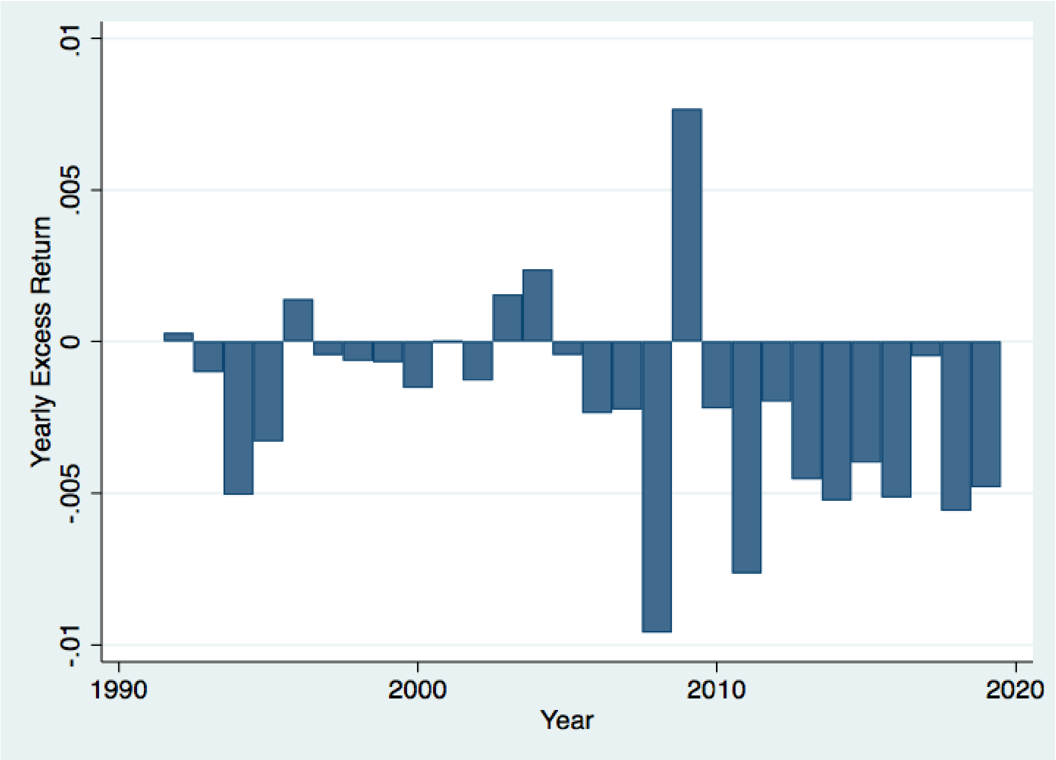


Figure 6 - Annual Long Portfolio Excess Return


Yearly Excess Return
.01
.005
0
-.005
-.01
1990
2000
2010
2020
Year