Earnings Surprises and the Cross-Section of Stock Returns

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Abstract

Do earnings surprises affect stock prices during the subsequent quarter? If so, what is the estimated impact, and to what extent can it be clearly distinguished from other factors? To answer these questions we build ten dynamic portfolios in which the companies are continuously reallocated according to their latest earnings surprise. A cross-sectional regression based on these portfolios indicates a distinct albeit nonlinear effect of the earnings surprise. To check whether the apparent effect of earnings surprises can be explained by other factors we test whether the renowned Fama-French three-factor model is able to explain the observed variation in returns across the portfolios. We then augment the Fama-French three-factor model with a factor based on earnings surprise and study the explanatory power of this fourth factor. By adding the forth factor the model is slightly improved. We also show that by "spanning" out the factors over more portfolios the model yields more reliable values. However, some issues arise associated to the linearity assumption of the model and thus we start to develop a nonlinear model. Finally, we present a simple trading strategy based on the spread between the positive and negative surprise portfolios.

Keywords: Earnings surprises, S&P 500, risk factors

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Introduction

This thesis sets out to examine earnings surprises and the cross-section of stock returns. More specifically, we study if earnings surprises affect stock prices during the quarter following an earnings announcement. Valuation theory has clearly shown that earnings are an important element in the valuation process of common stocks. A common valuation method is to use earnings times the appropriate multiplier for that risk class (Miller & Modigliani, 1966). With this in mind it is reasonable to assume that an earnings surprise should affect the stock price following the announcement. There are however several counter arguments, the main one being that there are other sources of information available to investors that contain essentially the same information but are more timely. It is intriguing that for example (Benston, 1967) finds that stock price changes are highly insensitive to earnings. However, (Beaver, 1968) raises the important fact that these results could simply be due to improperly specified expectation models.

Several researchers, amongst others (Ball & Brown, 1968), have found evidence of a relationship between earnings surprises and stock returns. They find that the price tends to drift in the same direction as the sign of the earnings surprise. Other researchers have in contrast found that a large portion of the stock price reactions move in the opposite direction of the earnings surprise (Kinney, et al., 2002).

It is not only in previous literature that earnings surprises is a highly debated topic. In a famous speech Arthur Levitt (1998), chairman of the Securities and Exchange Commission, expressed his concerns regarding the increasing pressure for firms to meet their estimates:

> "While the problem of earnings management is not new, it has swelled in a market that is unforgiving of companies that miss their estimates. I recently read of one major U.S. company, that failed to meet its so-called "numbers" by one penny, and lost more than six percent of its stock value in one day."

Earnings surprises have become very important for both managers and investors, especially for managers holding stock options in the company. There is also much focus on earnings estimates and surprises amongst analysts and media. Meeting or beating earnings forecasts doesn't only matter for the development of the stock price, it also builds credibility with investors and analysts.

In our study we construct ten dynamic portfolios in a way that to our knowledge has not been done before. The ten dynamic portfolios are formed from quarterly data for 284 U.S. firms. Portfolio limits are set so that each portfolio only consists of stocks with a certain level of earnings surprise. To avoid time lags we have programmed our portfolios to rebalance continuously, in contrast to earlier studies where portfolios are rebalanced on specific dates. That way we avoid several inclusion criteria that have constrained other researchers. At each firm's announcement date the earnings surprise is evaluated and the stock is allocated to the corresponding portfolio, in which it is subsequently held until that firm's next announcement date when it might again be reallocated. That way every stock is held in a portfolio for a whole quarter. At any point in time, the portfolio return is defined as the equally weighted return of the stocks that belong to that portfolio. The ten portfolios are tracked over the course of 26 years (1990-2015). The portfolio construction and calculations of returns are described in detail in the methodology section and in appendix A.

A cross-sectional regression based on these portfolios indicates a distinct, albeit nonlinear effect of the earnings surprise. These cross-sectional differences are a clear indication that earnings surprises do affect stock prices during the subsequent quarter. To check whether the apparent effect of earnings surprises can be explained by other factors we test whether the renowned Fama-French three-factor model is able to explain the observed variation in returns across the portfolios. We then augment the Fama-French three-factor model with a factor based on earnings surprise (henceforth called ESF) and study the explanatory power of this fourth factor.

From our results the Fama-French three-factor model helps us understand some of the differences in portfolio returns. There are however large and significant alphas indicating that market, size and value betas are not sufficient to explain all differences. When adding the ESF the model improves slightly, however mostly for the extreme portfolios. The risk premium for the ESF is positive and significant. Contrary to the Fama-French risk premia it is also stable over time. A potential implication of our results is a trading strategy that seeks to capture the spread in returns between firms reporting positive earnings surprises and firms reporting negative surprises.

Previous literature

Several researchers in both finance and accounting have studied earnings expectations and stock price movements around earnings announcements. The main focus for many has been to establish if earnings reports actually carry any informational value. (Ball & Brown, 1968) were the first to establish a relationship between earnings surprises and stock prices. In short, they wanted to study if the information reflected in income reports are useful. They argue that a large body of theory supports the proposition that capital markets are both efficient and unbiased. Thus, if information is useful in forming capital asset prices, then the market should adjust prices quickly, leaving no opportunity for arbitrage trade. Hence, by studying how stock prices are associated with the release of the income report they provide evidence that there are important information reflected in the income numbers. They find that the stock price change is associated with the sign of the forecast error (another definition of earnings surprise). They do not, however, study how the magnitude of the forecast error is related to stock prices. Furthermore, most of the movement in stock prices that they observed actually occurred *before* the announcement. Their dataset is somewhat limited in comparison to ours. They use yearly income for nine fiscal years (1957-1965) for 261 firms, which are substantially fewer data points than we have.

(Beaver, 1968) presents several arguments in his article to why stock prices drift prior to the announcement. Firstly, there are other available sources of information that are more timely than the income reports. Secondly, there could be measurement errors in the earnings or models could be improperly specified. He questions the findings of for example (Benston, 1967) who found that prices were largely insensitive to earnings. To avoid problems, he applied tests that didn’t require assumptions about expectations models of investors. He tried to see if any clustering of other news announcements around the earnings announcement date could explain the stock’s volume and price reactions. In conclusion he found no evidence that the price and volume reactions were attributable to the clustering of other news announcements. Thus, there must be at least some informational value in the earnings announcements.

Other researchers questioning the expectations models are (Foster, et al., 1984). They actually find that post-announcement drifts in stock prices are only present in a subset of earnings expectation models. However, the majority of studies do find a relation between earnings announcements and changes in stock prices.

(Rendelman Jr, et al., 1982) find similar results as (Ball & Brown, 1968) but use a different measure of earnings surprise. The definition used is the standardized unexpected earnings (SUE), where the earnings surprise is scaled by the standard deviation of the forecast error. They divide stocks into portfolio deciles from lowest to highest. Another thing they do differently from previous literature is that they construct their portfolio to have betas equaling one. That way they try to isolate only the SUE effect on abnormal returns. They find that there is an SUE effect on stock returns.

(Kinney, et al., 2002) build on previous literature presented and try to explore what magnitude of earnings surprise is required to trigger a significant market reaction. The time horizon of their dataset is limited compared to ours. They look at annual earnings surprises during a six year period (1992-1997). Returns are studied during a window that ranges between 22 days prior to the announcement until one day after the announcement. For the regressions they use five portfolio percentiles. They find that the overall relation between abnormal returns and earnings surprises are S-shaped. However, they also find contrarian reactions. That is, that the stock price moves in the opposite direction of the earnings surprise.

(Johnson & Zhao, 2012) dig deeper into the often overlooked phenomenon of contrarian stock price reactions. Their study provides evidence on the prevalence, determinants, and consequences of contrarian stock returns at the earnings announcement date. Their portfolios are divided into deciles ranked 1-10 and they scale earnings surprises by closing share price. Returns are studied in a three day window around the announcement. For as much as 40 % of the firms reporting each quarter Johnson and Zhao find contrarian stock movements. They also confirm that these results aren't a result of temporary mispricing, as the returns do not "reverse" in the next 240 trading days. Furthermore, the contrarian reactions are only slightly less prevalent in the extreme deciles.

In more recent years (Landsman & Maydew, 2001) redid Beaver's study. They believed that after thirty years there should be a degradation of the informativeness of earnings as the availability of timely non-accounting information has increased together with the increased technological innovation. However, what they found is on the contrary that the informativeness of earnings has increased over the past thirty years.

Data

This report is based on quarterly data from 1990 – 2015. The stocks analyzed are those included in the Standard & Poor's 500 (S&P 500). The constituents of the list have however changed over time and since we wanted to study the same firms at all times we have chosen those that are currently listed (as of February 2016). A side effect of this is that it might be a survivorship bias in our sample. Since all the companies included in the S&P are high performing, firms will be dropped from the index when they aren't fulfilling the criteria to be part of the index anymore. When only including "surviving" firms in a sample, results could be skewed. Moreover, companies that were listed after 1990 were removed. After removing all firms that lack data, 284 firms remained in our sample.

The main reason for choosing US firms is that the US market has the most extensive data available. Especially earnings estimates are difficult to find for other markets for a sufficiently long time-period. Earnings estimates are also difficult to find for smaller companies as analyst usually follow larger companies. The most accessible earnings forecasts were therefore for large-cap companies, like those of the S&P 500. Thus, while a wider selection of companies could have mitigated some of the biases discussed above it would inevitably have introduced other biases. In this trade-off we have chosen to prioritize completeness and reliability of data.

Daily closing prices for all stocks were downloaded from Thomson Reuter's Datastream. Prices were adjusted for dividends and for changes in number of stocks. The value-weighted return (including distributions) for all CRPS stocks in the US is used as a proxy for market return.

When studying earnings this report has focused on earnings per share (EPS). Other measures like revenue and operating profit might have been interesting, but lack of data forced us to look at the more accessible EPS. The mean of analysts' estimated EPS has been used as the consensus estimate. This proxy for market expectations was gathered together with actual EPS and date of announcement from the Institutional Broker's Estimate Service (I/B/E/S). Due to revisions in analyst's forecasts during a quarter I/B/E/S sometimes publishes several consensus estimates. To get the most accurate and updated expectation the last consensus estimate *before* the announcement date has been used.

Monthly risk-free rate and market risk premium were downloaded from Kenneth French's website. The size and value variables that they have calculated are however not applicable for us since we use a different sample. The data required to compute our own size and value variables, market capitalization and price-to-book, were accessed from Datastream.

Methodology

Earnings surprise

An earnings surprise is the difference between actual earnings and estimated earnings.
A common definition by other researchers is the standardized unexpected earnings. It is defined as the difference between actual earnings and estimated earnings scaled by the standard deviation of the forecast errors for that time period (Rendelman Jr, et al., 1982).

We could have used this, however we wanted a definition that was more commonly used in the "real world" by for example media and the average investor. It is not only easier to calculate but it is also easier to grasp. Our definition of earnings surprise is the (relative) over performance measure:

$$\text{Earnings surprise} = \frac{\text{Actual EPS} - \text{Estimated EPS}}{\text{Estimated EPS}} \tag{1}$$

Portfolio formation and calculation of returns

To look for cross-sectional differences we have created ten dynamic portfolios. Each portfolio consists at all times of stocks for which the most recent earnings surprise belongs to a pre-specified interval. The applied intervals are a static partition of $(-\infty, \infty)$ defined by a strictly increasing sequence of (nine) numbers. Dynamic partitions are also possible. One example could be to apply a rolling set of earning surprise percentiles. This would ensure that all portfolios had a stable number of firms which is an appealing property regarding numerical stability. However, it would blur the quantification of the earnings surprise effect, which is the major focus of this thesis. For this reason we have chosen to use a static partition. In other words, we define fixed intervals I_j where $j = 1, \ldots, 10$ and at each point in time a company belongs to portfolio *j* if the latest earnings surprise belongs to I_j (see figure 1). There are some cases where the "latest earnings surprise" is not defined. In particular, there is an initial part of the dataset (before any announcement has occurred). During this initial phase all the firms are allocated to a dummy portfolio. The returns of this dummy portfolio is however not interesting, as it quickly becomes empty.

Figure 1 – Portfolio limits and example of allocation

Ticker	Forecast period end date	Announcement date	Earning surprise
AAPL	19900331	19900421	0.236667
AAPL	19900630	19900718	0.143333
AAPL	19900930	19901020	-0.03667
AAPL	19901231	19910119	0.1425
MSFT	19900331	19900417	-0.14
MSFT	19900630	19900725	-0.1
MSFT	19900930	19901016	-0.03
MSFT	19901231	19910122	0.27
JNJ	19900331	19900426	-0.34857
JNJ	19900630	19900724	0.019231
JNJ	19900930	19901023	0.068182
JNJ	19901231	19910201	-0.02778

Lower limit	Portfolio	Upper limit
-Inf	0	-0.3
-0.3	1	-0.15
-0.15	2	-0.08
-0.08	3	-0.03
-0.03	4	0
0	5	0.03
0.03	6	0.08
0.08	7	0.15
0.15	8	0.3
0.3	9	+Inf

A company is assigned to portfolio J if the announced earning surprise (ES) in the interval $[LL_J, UL_J)$. Example: Johnson and Johnson is assigned to portfolio 6 because 0.068 is in that interval. Note that Apple is assigned to portfolio 4 because the lower level is inclusive.

In previous studies, e.g. (Ball & Brown, 1968), the authors have set a specific date each year when the portfolios are rebalanced. However, since most firms have different announcement dates this leads to a time-lag. It also means that firms reporting on a later date will not be included. This is another reason why we believe it is better to design our portfolios to be continuously rebalanced: At every announcement date, the corresponding firm is immediately[1] allocated to the portfolio corresponding to the obtained earnings surprise. The stock is then held for one quarter until the next announcement date when it is reevaluated on its earnings surprise.

Since our portfolios have fixed limits the announcement and reallocation of one stock does not affect the allocation of other stocks. However, as we use equally weighted portfolios, the relative influence of a firm on the portfolio returns will change each time a portfolio is involved in the rebalancing. See appendix A for more details.

[1] If the announcement date is not on a business, the reallocation is made on the first business day after the announcement.

Daily portfolio returns are calculated as the equally weighted return of the stocks that belong to that portfolio at that day:

$$\mathrm{AR}_{\mathrm{P,i,t}} = \frac{\sum_{\mathrm{n=1}}^{\mathrm{N}}(\mathrm{AR}_{\mathrm{i,t}} + \ldots + \mathrm{AR}_{\mathrm{N,t}})}{\mathrm{N}_{\mathrm{i,t}}} \tag{2}$$

Where: $\mathrm{AR}_{\mathrm{P,i,t}}$ = Abnormal return for portfolio *i* at time *t*

$\mathrm{AR}_{\mathrm{i,t}}$ = Abnormal return for stock *i* at time *t*

$\mathrm{N}_{\mathrm{i,t}}$ = Number of stocks in portfolio *i* at time *t*

Abnormal returns in equation (2) are calculated as:

$$\mathrm{AR}_{\mathrm{i,t}} = \mathrm{R}_{\mathrm{i,t}} - \mathrm{R}_{\mathrm{M,t}} \tag{3}$$

Where: $\mathrm{AR}_{\mathrm{i,t}}$ = Abnormal return for stock *i* at time *t*

$\mathrm{R}_{\mathrm{i,t}}$ = Return for stock *i* at time *t*

$\mathrm{R}_{\mathrm{M,t}}$ = Return for the market index at time *t*

Stock returns in equation (3) are calculated as:

$$\mathrm{R}_{\mathrm{i,t}} = \frac{\ln \mathrm{P}_{\mathrm{i,t}}}{\ln \mathrm{P}_{\mathrm{i,t-1}}} \tag{4}$$

Where: $\mathrm{R}_{\mathrm{i,t}}$ = Return for stock *i* at time *t*

$\mathrm{P}_{\mathrm{i,t}}$ = Stock price for company *i* at time *t*

$\mathrm{P}_{\mathrm{i,t-1}}$ = Stock price for company *i* at time *t-1*

Finally cumulative abnormal returns are calculated as:

$$\mathrm{CAR}_{\mathrm{i,t}} = \sum_{\mathrm{t=1}}^{\mathrm{T}} \mathrm{AR}_{\mathrm{i,t}} \tag{5}$$

Where: $\mathrm{CAR}_{\mathrm{i,t}}$ = Cumulative abnormal return for stock *i* at time *t*

$\mathrm{AR}_{\mathrm{i,t}}$ = Abnormal return for stock *i* at time *t*

Portfolio CARs are calculated in the same way as individual stock CAR in (5).

Risk factors

(Fama & French, 1992; 1993) argued that the Capital Asset Pricing Model (CAPM) wasn't sufficient to explain the cross-section of stock returns. They found that there were especially two classes of stocks that outperformed the market: companies with a small market capitalization[2] and companies with high book/market ratio[3]. Companies with a higher book/market ratio usually has a higher risk of financial distress, thus investors requires higher risk premia on those stocks. Small-cap companies carry more illiquidity risk, as they are not as frequently traded as large-cap firms. Hence, investors require a compensation for the risk they will carry from investing in illiquid assets. From their findings Fama and French created risk factors representing value (HML) and size (SMB). They then added the two factors to the CAPM model to reflect a portfolio's exposure to these two classes. The three-factor model had significantly more explanatory power of the cross-section of returns than CAPM had.

To explain any possible differences between our portfolio's returns we thus use the three-factor model as our starting point. The size and value variables do not exist for our sample and has been manually calculated according to the procedures specified by Fama and French. All factors are calculated on a monthly basis.

[2] Market capitalization = Share price x number of shares outstanding

[3] Book/market = Book value of common stock/market capitalization

The size factor: SMB (small minus big), the return for the 50% smallest companies minus the return for the 50% largest companies.

The value factor: HML (high minus low), the return for the companies with the 30% highest book/market value minus the return for the companies with the 30% lowest book/market.

Each portfolio's excess return is regressed in the three-factor model:

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_{i,Mktrf}(R_{M,t} - r_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \epsilon_{i,t} \quad (6)$$

Where *i* is the index of the portfolios and *t* is an index for time periods.

With the same reasoning Fama and French used when creating SMB and HML we proceed and add an additional factor. If portfolios with companies that beat their earnings estimates show signs of outperforming portfolios with companies that miss their estimates it is possible that a factor related to the earnings surprise might add value to the three-factor model.

The earnings surprise factor: ESF, the return for the companies with a positive earnings surprise of 15% or more minus the return of the companies with a negative earnings surprise of -15% or less.

Each portfolio's excess return is then regressed in the four-factor model:

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_{i,Mktrf}(R_{M,t} - r_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,ESF}ESF_t + \epsilon_{i,t} \quad (7)$$

Where *i* is the index of the portfolios and *t* is an index for time periods.

(Fama & MacBeth, 1973) developed a robust methodology to test these types of factor models empirically. The method is used to find beta values and risk premia (lambdas). It can be applied to any risk factors that could affect the excess returns of assets and/or portfolios.

We run a two-stage regression for the three-factor and the four-factor model according to Fama-Macbeth. The first stage is the time-series regression in equation 6 and 7. Each portfolio is regressed against the proposed risk factors to determine that portfolio's beta for that risk factor. The number of regressions is thus equal to the number of portfolios, in our case ten. The first pass regression tells us how the portfolios excess returns are affected by each risk factor.

In the second stage we run monthly cross-sectional regressions. All portfolio returns for a fixed time period are regressed against the estimated betas to determine the risk premium for each factor. The number of regressions is thus equal to the number of time periods.[4] The $\hat{\beta}$s are defined as the estimated betas from the regressions in the first pass regression. Note that these are independent variables that will be the same in all of the regressions. The lambda values are the coefficients representing the risk premia investors get.

$$R_{i,t} - r_{f,t} = \lambda_{i,t} + \lambda_{Mktrf,i,t}\hat{\beta}_{i,Mktrf} + \lambda_{SMB,i,t}\hat{\beta}_{i,SMB} + \lambda_{HML,i,t}\hat{\beta}_{i,HML} + \epsilon_{i,t} \tag{8}$$

$$R_{i,t} - r_{f,t} = \lambda_{i,t} + \lambda_{Mktrf,i,t}\hat{\beta}_{i,Mktrf} + \lambda_{SMB,i,t}\hat{\beta}_{i,SMB} + \lambda_{HML,i,t}\hat{\beta}_{i,HML} + \lambda_{ESF,i,t}\hat{\beta}_{i,ESF} + \epsilon_{i,t} \tag{9}$$

Where *i* is the index of the portfolios and *t* is an index for time periods.

Finally, to test if the ESF is an independent variable we regress the excess return of the factor in the Fama-French three-factor model:

$$ESF - r_{f,t} = \alpha + \beta_{Mktrf}(R_{M,t} - r_{f,t}) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \epsilon_t \tag{10}$$

[4] Since most portfolios are empty during the first months in 1990 (before all companies have reported for the first time) we have used 1991-2015 as our sample period for the factor analysis.

Results

Portfolio returns

Figure 2 – Portfolio CAR over time

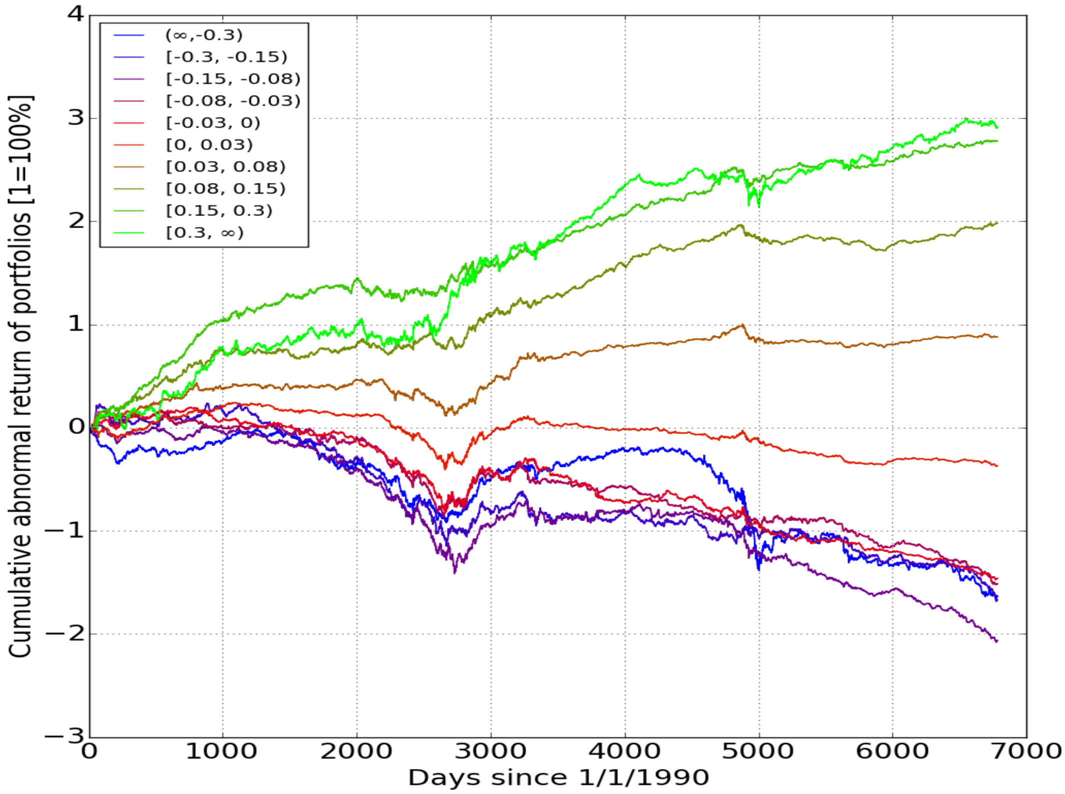

Figure 2 plots the CAR for all portfolios. Each line represents one portfolio, and the legend displays the earnings surprise intervals associated with each of the portfolios. Blue shades means negative, red shades means neutral and green shades means positive earnings surprises.

Looking at figure 2 it is evident that the relative behavior of the portfolios' cumulative abnormal returns varies with time. Thus a cross-sectional regression based on the CAR during 1990 to 2000 would not give the same results as a regression based on 2005 to 2015. However, the general pattern seems to hold over a period of 8 years (3000 days) or more. The portfolios with positive earnings surprises generally outperform both the market and the portfolios with negative surprises. The sign of the surprise thus seems to be important for stock returns. Regarding the effect of the magnitude the conclusion is different between positive and negative surprise portfolios. The dispersion between each portfolio is greater for the positive surprise portfolios. It seems like more positive surprises yield higher CAR than less positive surprises. In contrast, the negative surprise portfolios are more bundled together. Apparently the market punishes firms that fail to live up to their expectations almost equally hard no matter by how much they miss.

Table 1 breaks down portfolio returns into annual CAR. It further highlights the differences between positive and negative surprise portfolios. All five of the negative surprise portfolios yield a negative annual CAR on average. Interesting is however that portfolio 5, with earnings surprises ranging between 0 and 3 %, also has a negative yearly mean CAR. It does not seem to be sufficient to merely meet your estimates. This is surprising, as previous literature tends to find that meeting or beating estimates with small amounts yield positive stock price reactions (Ball & Brown, 1968).

Table 1 – Summary statistics for the portfolios yearly CAR

Portfolio index		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
count (years)		26	26	26	26	26	26	26	26	26	26
mean		-0.06298	-0.06426	-0.07945	-0.05827	-0.05619	-0.01427	0.033875	0.076211	0.106838	0.111822
std		0.168083	0.117952	0.141252	0.125416	0.105199	0.093699	0.075912	0.08262	0.105248	0.147887
min		-0.4908	-0.33089	-0.44817	-0.38987	-0.28235	-0.27207	-0.10499	-0.0564	-0.08777	-0.14011
	25%	-0.20066	-0.1156	-0.13826	-0.09826	-0.11806	-0.05034	-0.00739	0.018011	0.046938	0.034391
	50%	-0.03593	-0.04962	-0.06499	-0.05399	-0.06533	-0.02412	0.024554	0.072712	0.091006	0.090994
	75%	0.040786	-0.01482	0.007524	-0.00378	0.002052	0.017086	0.056085	0.140434	0.142666	0.147367
max		0.262004	0.119731	0.253664	0.285626	0.189832	0.193941	0.199838	0.213709	0.341516	0.596533

Table 1 gives an overview of the descriptive statistics of the portfolios' annual cumulative abnormal returns (CAR). The range varies from 0.3-0.75 and the inter quartile range (IQR) varies from 0.10-0.25. The average annual CAR is quite monotonous as a function of earnings surprise (see also figure 3).

Standard deviation appears to be rather similar across the portfolios. The exceptions are the two "extreme" portfolios which both have higher standard deviations. Generally there is a lower standard deviation for the positive surprise portfolios compared to the negative surprise portfolio with the same absolute limits.

Figure 3 – Average annual CAR as a function of earnings surprise

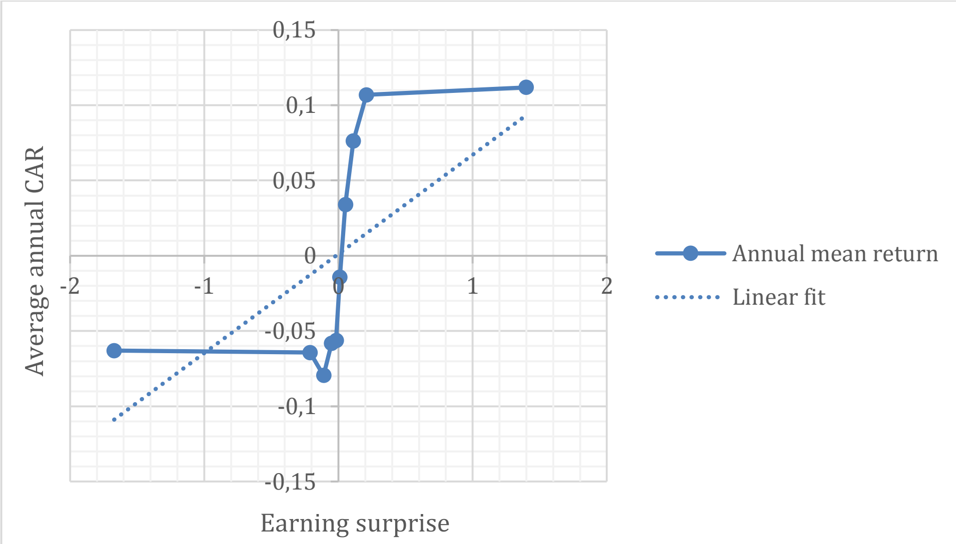

Figure 3 plots the relationship between each portfolio's average annual CAR and its earnings surprise. The earning surprise values are the average surprise for each portfolio. Note that the two extreme points correspond to the half open end intervals used to define the portfolios which is why they are located far away from the other points. A linear regression line is included but it obviously does not fit the data.

The graph in figure 3 clearly shows an S-shaped relationship between earnings surprises and abnormal returns (Kinney, et al., 2002). The sigmoid relationship is as discussed previously evident for positive surprises while it is noisier for negative surprises. The p-value and other statistics of a *linear* regression will hardly be significant because the linear model does not fit the data. The significance of the earning surprise effect is indisputable from visual inspection – it's just nonlinear. Any properly chosen nonlinear parametrization, e.g. a hyperbolic tangent function would be statistically significant. For an example of this see appendix C.

Figure 4 shows a clear trend that companies have tended to report more positive earnings surprises throughout the observation period. During 1990-2000 the median surprise fluctuated around zero, meaning that around 50 % of the firms reported positive surprises and 50 % reported negative surprises. After the dot com bubble crashed in 2001 the median surprise has instead fluctuated between two and three percent. The trend becomes even more evident when looking at the 30th percentile. This trend is especially interesting given that the infomativeness of earnings has increased over the last 30 years (Landsman & Maydew, 2001). We leave speculations if this development is due to analysts becoming more pessimistic, managers engaging more in earnings/expectations management or other reasons left unsaid.

Figure 4 – Earnings surprise percentiles over time

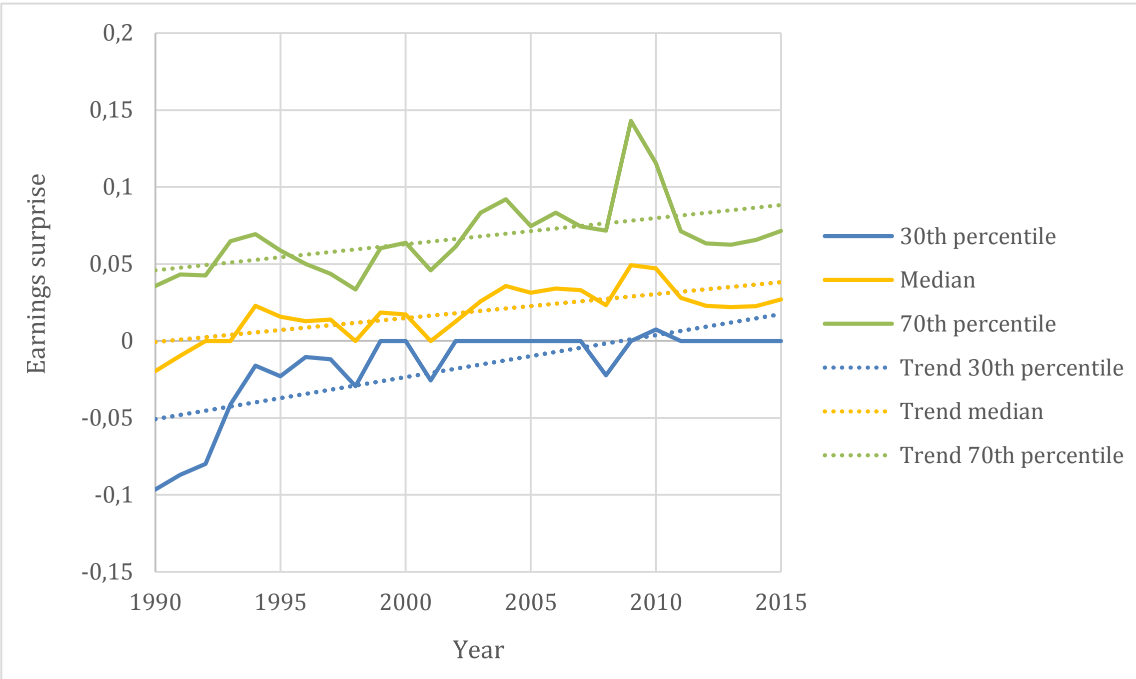

Figure 4 depicts annual average earnings surprises from our sample between the years 1990-2015.

Risk factor analysis

Table 4 and 5 show the results from the first pass regression for the Fama-French three-factor model and the Fama-French model including the ESF. The market beta is relatively stable across the portfolios. It is positive and statistically significant and ranges between 0.85 and 1.08. There are no clear patterns to help explain the differences in portfolio returns. The HML beta is also rather stable across the portfolios. It ranges from 0.14 to 0.50 and is significant for all portfolios. There is however a general pattern of negative surprise portfolios having a slightly larger exposure to the HML factor compared to positive surprise portfolios. For the SMB beta there is on the other hand large variations across the portfolios, ranging from 0.01 to 0.81. The value is, however, not significant for all portfolios. This might be due to the fact that our sample mainly consists of large cap stock. Another observation is that the SMB beta is higher for portfolios with higher absolute values of the earnings surprise. This could indicate that relatively smaller companies have a higher tendency to report earnings surprises of larger magnitude.

The R-square is relatively high for all portfolios, ranging from 0.7 to 0.85. There is however, for eight out of ten portfolios a statistically significant alpha clearly distinguished from zero. The alphas also have a noticeable correlation with the portfolio number (i.e. the size and magnitude of the earnings surprise) which suggests that earnings surprises are like to play an important role in explaining the differences in portfolio returns. Thus, even though the R-square is high and the factors generally are significant the Fama-French model is not able to explain all the variability in returns.

When including the ESF the market beta increases slightly for the negative surprise portfolios while decreasing slightly for the positive surprise portfolios. The changes are however minor. For SMB and HML the opposite occur but the changes are again minor. The ESF factor only has statistical significance for 5 of 10 portfolios and mainly for the "extreme" portfolios. Accordingly, R-square mostly increases for these portfolios. The reason why the ESF does a better job explaining the more extreme portfolios is most likely the S-shaped relationship between earnings surprises and returns. There still remains an alpha for 7 out of 10 portfolios.

The fact that the Fama-French factors aren't affected much by adding the ESF suggests that ESF is not overlapping the other factors. This belief is further strengthened by the large and significant alpha that can be observed when ESF is regressed on the Fama-French model. The results from this regression are found in table 6. The links between the ESF and the market, size and value factors can also be seen in the cross-correlations in table 7. The ESF is positively associated with the market but negatively associated with size and value. The correlations are however low and we thus conclude that ESF should be treated as an independent explanatory variable.

Table 8 and 9 show risk premia for the risk factors from our Fama-Macbeth second pass regression for the full time period. Table 10 presents the risk premia for the four-factor model for two sub-periods. The ESF is positive and significant for all time periods. The Fama-French factors are on the other hand more volatile. These numbers should however be treated with care. Previous papers have found that if factors aren't sufficiently "spanned out" by the assets, the risk premia values may be misleading (Hou & Kimmel, 2010; Kan & Robotti, 2011; Kan & Zhang, 1999). The ten portfolios are possibly too few to get reasonable risk premia. The lambda value for HML is for example negative and significant. For that reason we tried to add Fama-French's 25 portfolios sorted on size and book to market. The results are found in table 11 and 12. Overall the results are now more reasonable, confirming that the additional portfolios are needed when examining risk premia.

One effect of adding the new portfolios is that the HML premium is now positive as one would expect. Observe that the ESF premium is not affected by adding the new portfolios, because this factor was fully spanned by the ten original portfolios. There are however still unexplained parts and a positive and significant alpha. The most reasonable explanation, which is presented by the abovementioned authors is that the model we use is linear. This seems to be an improper model set up for earnings surprises. While the Fama-French factors are linear, earnings surprises follow a nonlinear pattern. The papers mentioned have found that if models are improperly set up in regard to the data it usually leads to problems when estimating risk premia.

Possible trading strategy

Based on the findings outlined in this paper we present some simple calculations on an "earnings surprise" trading strategy. A strategy of buying stocks with positive earnings surprises of 15% or more and shorting stocks with negative earnings surprises of -15% or more, i.e. going long the ESF, earned an average return of 2.86% per month during our sample period. This is substantially higher than for a size or value strategy. The standard deviation is however also higher. Table 13 shows descriptive statistics of monthly returns for the factors. The large positive and significant alpha in table 6 means that the high return is not simply due to high exposure to the common Fama-French factors.

It should however be noted that these calculations are done without taking trading costs into account. A strategy based on earnings surprises would be costlier than a "size" or "value" strategy due to the need to rebalance more frequently. Our portfolios are constructed on the assumption that we buy, hold the stock for one quarter, and then sell - unless the next earnings surprise happens to be in the same portfolio interval.

Conclusion

The effect of earnings surprises on stock returns is a well-documented area in academia. The methods used are however different and the findings somewhat contrarian. By constructing dynamic portfolios this paper avoids several of the constraints that previous literature has faced in their sample selection. We also use a simpler definition of earnings surprise with the hope of making the results more understandable. Our findings support the S-shaped relationship between earnings surprises and stock returns that (Kinney, et al., 2002) found in their paper. Interesting however, is that we find no clear differences between the returns of the five negative surprise portfolios. Furthermore, our results show an upward shift towards companies reporting more positive earnings surprises than before. A potential implication of the results in this paper is a trading strategy that seeks to capture the spread in returns between firms reporting positive earnings surprises and firms reporting negative surprises.

The Fama-French three-factor model can help us understand some of the differences in portfolio returns. There are however large and significant alphas indicating that market, size and value betas are not sufficient to explain all differences. When adding the ESF the model improves slightly, though mostly for the extreme portfolios. The risk premium for the ESF is positive and statistically significant. The economic interpretation of the factor is that investors face a risk when they hold stocks over earnings announcements. We have shown that stock prices tend to move in the same direction as the earnings surprise. Aware of this, but unable to predict with certainty the magnitude or sign of the surprise, investors will require a premium as compensation for this risk.

One problem with both the three-factor and four-factor model is the nonlinear relationship between earnings surprises and stock returns. The Fama-French model, like most asset pricing models builds on linearity. We have started to develop a basic nonlinear model that explains the relationship between earnings surprises and CAR (see appendix C), however this is something that falls outside the scope of this paper. Suggestions for further studies are therefore to develop a nonlinear model, which could work as an alternative model to Fama-French's.

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Appendix A – Definition of the portfolios

The portfolios are designed to reflect the earnings surprise. The number of portfolios should on one hand be large to allow for a high resolution in representing earnings surprise, but this has to be balanced by the need for ensuring a sufficient number of companies in all categories. As a compromise we arrived at 10 portfolios.

The 284 companies included in our study were all initially allocated to a "dummy" portfolio labelled -1. Then they are allocated to one of the 10 portfolios (labelled 0-9) according to earnings surprises as they are announced.

For each company we define a daily portfolio index. If this index has value j at time t it means that the latest announced earnings surprise before time *t* was mapped to portfolio *j*. The index then stays at this value until a future earnings surprise evaluates to a different portfolio index.

The mapping rule is defined by 10 intervals $I_j = [LL_j, UL_j), j = 0, \dots, 9$ where the limits obey the rule $LL_{j+1} = UL_j$ with the obvious exceptions of the end points where the intervals are half open. In other words the portfolios are defined by the 9 values $LL_j, j = 1, \dots, 9$. The principle for choosing limits is to let resolution follow variability. As the impact from earnings surprise on expected returns appear to be quite nonlinear it is important to have highest resolution around the transition point which is around zero earnings surprise level. Our final choice for intervals is summarized in table 2 below:

Table 2 – Portfolio limits

Lower limit	**Portfolio**	**Upper limit**
-Inf	0	-0.3
-0.3	1	-0.15
-0.15	2	-0.08
-0.08	3	-0.03
-0.03	4	0
0	5	0.03
0.03	6	0.08
0.08	7	0.15
0.15	8	0.3
0.3	9	+Inf

Table 2 shows the lower and upper limits for each portfolio. The portfolios are indexed from 0 to 9 with portfolio 0 being the one with most negative surprises.

For example, if the earnings surprise at time t turns out to be 0.015 for company k, it would be allocated to portfolio 5 because $0.015 \in [0, 0.03)$. Its portfolio index, $PFI_{k,t}$ would then be assigned the value 5 for all days from t until a future announcement would be mapped to a different portfolio.

The Python module performs this allocation for all 284 companies which results in a portfolio index matrix PFI. The logic is illustrated in figure 5. Using equally weighted portfolios, the average daily return for each portfolio can be obtained by averaging the return for all companies belonging to the portfolio. The portfolio index matrix can be used as a selector for calculation of the average return. See the following code segment as an illustration.

```
for i in range(len(returns)):
    for j in range(nportfolios):
        if np.size((np.where(pfind[i]==j)))>0:
            pfret[i,j]=np.mean(returns[i,np.where(pfind[i]==j)])
        else:
            pfret[i,j]=0
```

The result is a matrix with daily portfolio returns, PFR_{tk}, having 6784 rows (=number of days) and 10 columns (=number of portfolios).

Figure 5 – Example of the reallocation process

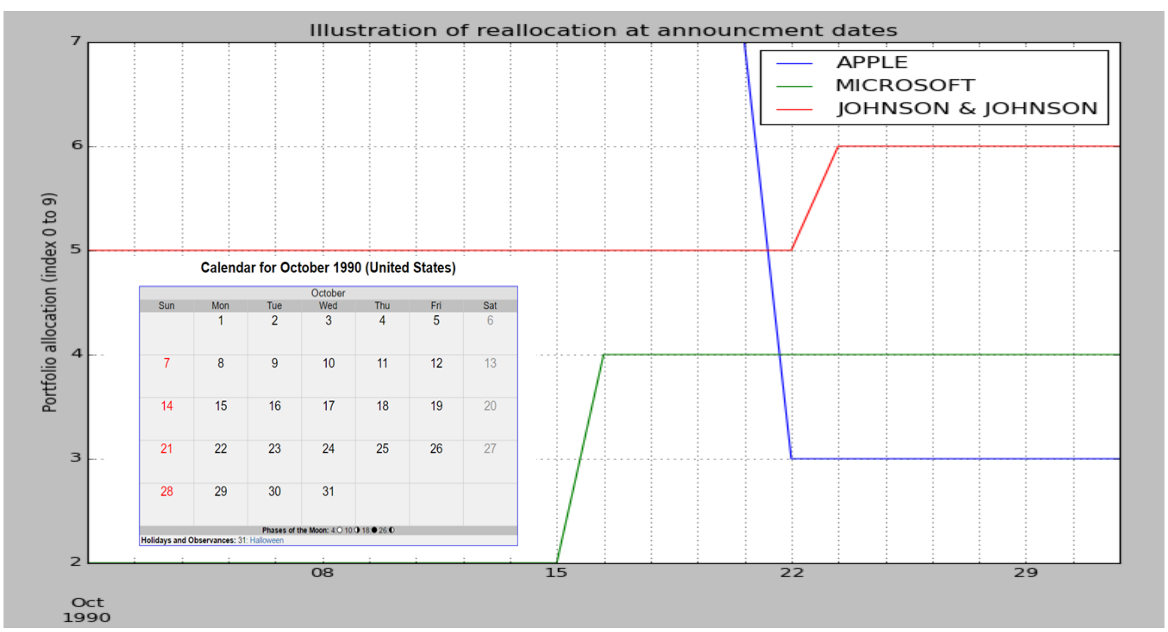

Figure 5 shows how the companies – exemplified by Apple, Microsoft and Johnson & Johnson – each reallocate from one portfolio to another during their announcements in October 1990. Note that the transition takes place on the first business day after (or equal to) the announcement date.

While Microsoft and Johnson & Johnson is reallocated ON the announcement dates (16/10 and 23/10 respectively), observe that the Apple announcement was on a Saturday and that the transition takes place on Monday 22/10.

Figure 6 – Variability of portfolio allocation for selected companies during 2000 - 2010

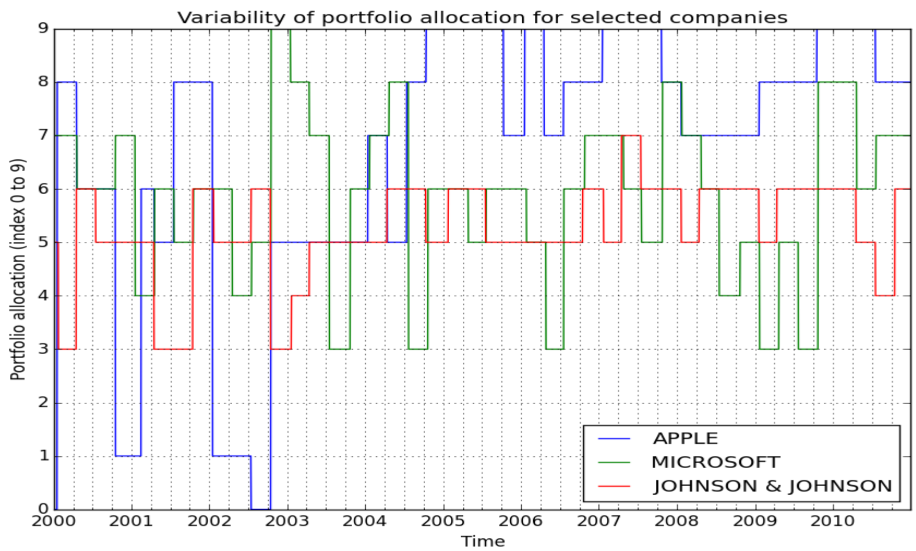

Figure 6 illustrates how the allocation of selected companies varies across time. Some companies, like Apple may move from one extreme to another in just a few years, while other companies, like Johnson & Johnson have a more stable behavior. The portfolio indices 0-9 can be looked upon as an ordinal scale for earnings surprise. Apple thus disappointed the market in 2002 while consistently beating the expectations in 2005.

The portfolio distribution among companies obviously varies across time as illustrated in figure 6. However, from the descriptive statistics in table 3 it is clear that the monthly average of number of companies in each portfolio is almost never lower than 4-5 companies, and the 25 percentile typically has more than 10 companies in each portfolio. As can be seen in table 3 and figure 7, portfolio 5 and 6 have a little more firms than the rest while portfolio 1 and 2 have a little less. Overall there are generally more firms in the portfolios with positive surprises which may create somewhat more stable returns than for those with negative surprises. We can however conclude that the number of companies in each portfolio is not so low that it would affect the reliability of the results.

Table 3 – Descriptive statistics of portfolio contents during 1991-2015

Portfolios	0	1	2	3	4	5	6	7	8	9
Months	300	300	300	300	300	300	300	300	300	300
Mean	17.45	11.75	12.89	19.28	16.96	62.40	43.62	27.45	21.59	17.96
Sd	7.73	4.28	4.61	5.15	5.57	15.50	13.02	8.93	6.92	7.67
Min	5.61	2.67	1.91	6.00	5.00	24.71	10.76	7.80	5.77	5.73
5%	7.73	5.05	5.00	10.82	8.56	33.68	20.52	13.54	11.98	9.39
10%	9.63	6.59	6.61	12.00	10.00	38.32	27.47	15.66	13.36	11.30
25%	12.00	8.76	10.04	16.08	12.52	50.63	34.13	21.48	16.64	13.64
50%	15.40	11.62	12.95	19.55	16.86	65.13	43.92	27.42	21.23	16.12
75%	21.97	14.06	15.72	22.62	20.96	74.32	54.30	33.33	25.48	20.00
Max	43.64	22.87	23.95	31.73	30.90	91.55	70.45	54.59	44.13	54.35

Table 3 summarizes the average number of companies in each portfolio per month. Earnings surprises are somewhat skewed towards positive values. Red (green) means lower (higher) than average number of companies in the portfolio, and we see that there are slightly more companies in portfolio 5-9 than in portfolio 0-4. Portfolio 5 has slightly more companies because it contains the value 0, i.e. when the announced earnings surprise exactly matches the consensus estimate.

Figure 7 – Distribution among the portfolios

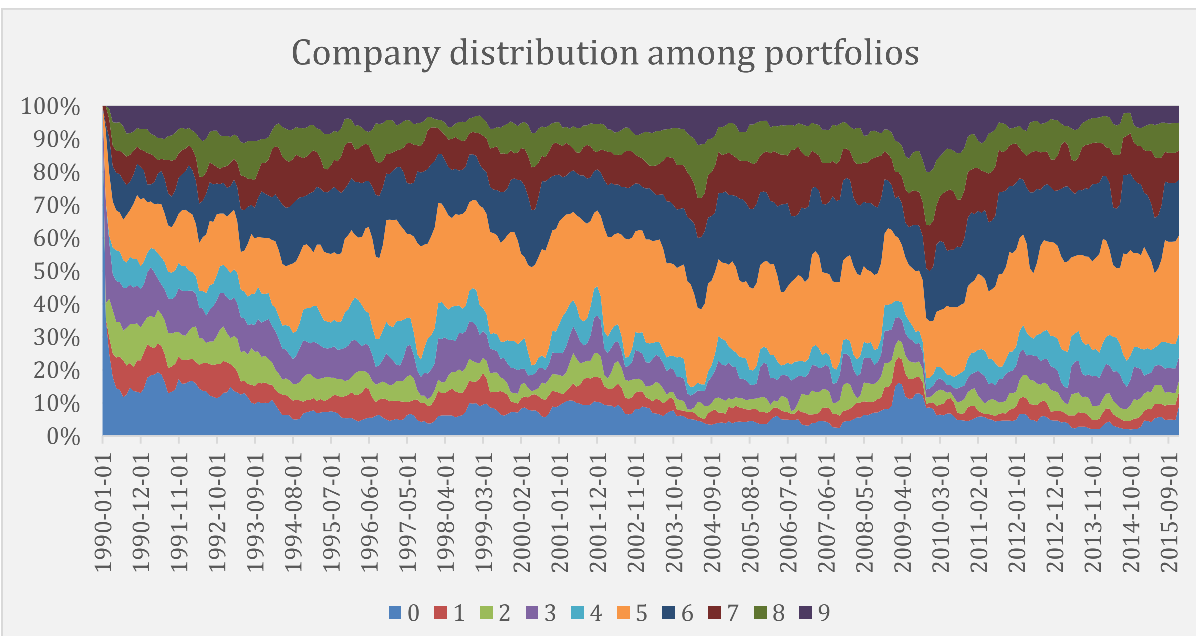

Figure 7 shows the relative distribution of companies in each portfolio across time. The patterns are fairly stable with the apparent exception of the financial crisis in 2008 and the subsequent rebound in 2009.

Appendix B – Tables

Table 4 – First pass regression, three-factor model

VARIABLES (β)	(1) exc_ret0	(2) exc_ret1	(3) exc_ret2	(4) exc_ret3	(5) exc_ret4	(6) exc_ret5	(7) exc_ret6	(8) exc_ret7	(9) exc_ret8	(10) exc_ret9
Mktrf	1.046***	0.857***	0.877***	0.900***	0.865***	0.851***	0.889***	0.913***	0.987***	1.084***
	(0.0558)	(0.0512)	(0.0458)	(0.0398)	(0.0551)	(0.0351)	(0.0335)	(0.0336)	(0.0377)	(0.0505)
SMB	0.703***	0.538***	0.305**	0.265***	0.00921	0.160	0.206*	0.210***	0.215**	0.811***
	(0.0973)	(0.125)	(0.145)	(0.102)	(0.199)	(0.0972)	(0.105)	(0.0774)	(0.106)	(0.137)
HML	0.491***	0.500***	0.491***	0.425***	0.413***	0.234***	0.141**	0.217***	0.172***	0.338***
	(0.0911)	(0.0914)	(0.0946)	(0.0855)	(0.106)	(0.0742)	(0.0659)	(0.0605)	(0.0597)	(0.0745)
Constant	-1.276***	-1.192***	-1.158***	-0.996***	-0.789***	-0.360***	-0.0107	0.268**	0.512***	0.145
	(0.190)	(0.192)	(0.180)	(0.152)	(0.200)	(0.115)	(0.114)	(0.125)	(0.144)	(0.185)
Observations	300	300	300	300	300	300	300	300	300	300
R-squared	0.785	0.701	0.700	0.729	0.696	0.825	0.846	0.795	0.766	0.755

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: The excess returns for each of the ten portfolios are regressed against the Fama-French factors. The table shows the beta values for all factors with the robust standard errors in parenthesis. The market beta varies little among the portfolios. HML are significant for all portfolios and SMB is significant for most portfolios. R-square is fairly high, but somewhat lower for the portfolios with moderately negative earnings surprises. The alpha has a noticeable correlation with the portfolio number (i.e. earnings surprise level) indicating that this variable is a strong candidate for explaining some of the residual variance.

Table 5 – First pass regression, four-factor model

VARIABLES (β)	(1) exc_ret0	(2) exc_ret1	(3) exc_ret2	(4) exc_ret3	(5) exc_ret4	(6) exc_ret5	(7) exc_ret6	(8) exc_ret7	(9) exc_ret8	(10) exc_ret9
Mktrf	1.088***	0.891***	0.887***	0.906***	0.869***	0.857***	0.890***	0.906***	0.945***	1.034***
	(0.0510)	(0.0517)	(0.0466)	(0.0401)	(0.0555)	(0.0356)	(0.0344)	(0.0330)	(0.0323)	(0.0444)
SMB	0.648***	0.495***	0.292**	0.257**	0.00413	0.153	0.204*	0.219***	0.268***	0.875***
	(0.0949)	(0.119)	(0.146)	(0.101)	(0.201)	(0.0977)	(0.106)	(0.0784)	(0.0875)	(0.103)
HML	0.369***	0.403***	0.462***	0.408***	0.402***	0.217***	0.137**	0.238***	0.291***	0.481***
	(0.0677)	(0.0825)	(0.0980)	(0.0881)	(0.105)	(0.0743)	(0.0640)	(0.0641)	(0.0609)	(0.0634)
ESF	-0.253***	-0.202***	-0.0598*	-0.0356	-0.0237	-0.0350	-0.00901	0.0426	0.247***	0.298***
	(0.0432)	(0.0450)	(0.0356)	(0.0388)	(0.0356)	(0.0284)	(0.0220)	(0.0265)	(0.0325)	(0.0375)
Constant	-0.484***	-0.562***	-0.971***	-0.885***	-0.715***	-0.250*	0.0175	0.135	-0.260	-0.786***
	(0.172)	(0.213)	(0.210)	(0.191)	(0.231)	(0.139)	(0.118)	(0.163)	(0.159)	(0.210)
Observations	300	300	300	300	300	300	300	300	300	300
R-squared	0.841	0.747	0.704	0.730	0.696	0.828	0.846	0.798	0.840	0.826

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: The excess returns for each of the ten portfolios are regressed against the Fama-French factors augmented by the earnings surprise factor. The table shows the beta values for all factors with the robust standard errors in parenthesis. The market beta varies little among the portfolios. HML are significant for all portfolios and SMB is significant for most portfolios. R-square is fairly high, but somewhat lower for the portfolios with moderately negative earnings surprises. The R-square is slightly higher than in the three-factor model, especially for the "extreme" portfolios. However, note that the alpha is no longer correlated with the earnings surprise, but rather has polynomial shape. This may be attributable to a nonlinear relation between the earnings surprise and the portfolio returns.

Table 6 – Regression analysis of the ESF factor

VARIABLES (β)	(1) ESF
Mktrf	0.168*
	(0.0911)
SMB	-0.214
	(0.227)
HML	-0.481***
	(0.154)
Constant	3.122***
	(0.335)
Observations	300
R-squared	0.099

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 presents the results of the second pass regression of the long-short earnings surprise factor on the Fama-French three-factor model. The HML coefficient is statistically significant. Most importantly, the R-squared is negligible and the alpha value is significant.

Table 7 – Correlation between the factors

	ESF	Mktrf	SMB	HML
ESF	1.0000			
Mktrf	0.1325	1.0000		
SMB	-0.1631	0.1733	1.0000	
HML	-0.2884	-0.0761	0.4745	1.0000

Table 7 shows the correlation matrix for the four-factors applied in the regression models. There is some correlation between HML and SMB, and the negative correlation indicated by the significant negative regression coefficient in Table 6 is reflected in the negative correlation term for HML and ESF. Still, the condition number of the correlation matrix is about 3.5, so collinearity appears not to be an issue. Accordingly, the earnings surprise factor can be treated as linearly independent of the other factors.

Table 8 - Fama-MacBeth second pass regression, three-factor model

VARIABLES (λ)	(1) Excess Portfolio Return
Mktrf	3.245***
	(0.936)
SMB	0.404
	(0.353)
HML	-3.677***
	(0.392)
Constant	-1.383*
	(0.790)
Observations	3,000
Number of groups	300
R-squared	0.239

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

Table 8 shows the risk premia estimates from the second pass Fama-MacBeth regression for the Fama-French three-factor model. The large and negative value for HML is uncommon and is a sign that there may be insufficient information in the dataset to estimate all the parameters satisfactorily.

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Table 9 - Fama-MacBeth second pass regression, four-factor model

VARIABLES (λ)	(1) Excess Portfolio Return
Mktrf	1.093
	(1.188)
SMB	0.737*
	(0.384)
HML	-2.781***
	(0.408)
ESF	2.984***
	(0.333)
Constant	0.195
	(0.977)
Observations	3,000
Number of groups	300
R-squared	0.304

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

Table 9 shows the risk premia estimates from the second pass Fama-MacBeth regression for the Fama-French three-factor model augmented with the earnings surprise factor (ESF). The risk premium for the ESF is positive and significant. On the other hand, the large and negative value for HML is uncommon and is a sign that there may be insufficient information in the dataset to estimate all the parameters satisfactorily.

Table 10 - Fama-MacBeth second pass regression, four-factor model, during two sub-periods

VARIABLES (λ)	(1991-2002) Excess Portfolio Return	(2003-2015) Excess Portfolio Return
Mktrf	-0.0902	1.766**
	(1.797)	(0.780)
SMB	0.0934	-2.403***
	(0.390)	(0.394)
HML	-1.751**	0.917**
	(0.677)	(0.397)
ESF	3.068***	2.720***
	(0.569)	(0.365)
Constant	1.413	-0.573
	(1.368)	(0.674)
Observations	1,440	1,560
Number of groups	144	156
R-squared	0.300	0.303

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

Table 10 shows the second pass regression parameters evaluated in two non-overlapping periods. The calculations are based on the 10 portfolios calculated from earnings surprise. The estimated risk premium associated with the ESF is stable across time periods. The same is true for the R-squared. Meanwhile, the other parameter estimates are fluctuating. One reason for this can be that the 10 portfolios don't "span" the factors sufficiently. The other reason may be model misspecification – the relationship between ESF and portfolio return is nonlinear while the Fama-MacBeth regression is based on linear terms. However, the stability across time supports that there is a sustained effect of earnings surprise on portfolio returns.

Table 11 - Fama-MacBeth second pass regression, three-factor model, with 25 Fama-French portfolios added

VARIABLES (λ)	(1) Excess Portfolio Return
Mktrf	-0.385
	(0.399)
SMB	0.306*
	(0.174)
HML	-0.0563
	(0.237)
Constant	0.915***
	(0.306)
Observations	10,500
Number of groups	300
R-squared	0.347

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

Table 11 shows the risk premia estimates from the second pass Fama-MacBeth regression for the Fama-French three-factor model) when the ten portfolios based on earnings surprise are augmented with 25 portfolios sorted on size and book/market. Few of the estimates are significant except the alpha. This suggests that there are unexplained factors.

Table 12 - Fama-MacBeth second pass regression, four-factor model, with 25 Fama-French portfolios added

VARIABLES (λ)	(1) Excess Portfolio Return
Mktrf	-0.541
	(0.400)
SMB	0.482***
	(0.174)
HML	0.146
	(0.240)
ESF	3.000***
	(0.342)
Constant	0.941***
	(0.306)
Observations	10,500
Number of groups	300
R-squared	0.387

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

Table 12 shows the risk premia estimates from the second pass Fama-MacBeth regression for the Fama-French three-factor model augmented with the earnings surprise factor (ESF) and with the 25 portfolios sorted on size and book/market added to our 10 portfolios. Interestingly, and in contrast to the regression with only ten portfolios (table 9), the SMB and HML figures are now more in line with consensus values. The ESF risk premium is large, significant and almost equal to the case with only 10 portfolios. This suggests that the added assets were necessary to yield more reliable values for the SMB and HML risk premia. However there is still a significant alpha, implying that the model fails to describe all the variations in the portfolio returns.

Table 13 – Descriptive statistics over monthly factor returns (%)

VARIABLES	(1) N	(2) Mean	(3) Sd	(4) Min	(5) max
Mktrf	300	0.669	4.279	-17.23	11.35
SMB	300	0.542	1.809	-8.071	9.057
HML	300	0.539	2.939	-10.11	11.89
ESF	300	2.862	5.725	-22.28	27.63

Table 13 displays descriptive statistics for the monthly factor returns. In particular, the mean value should in theory be close to the estimated risk premia estimates from the second pass Fama-Macbeth regression. This is true for the most significant estimates in table 12 – the ESF and SMB variables.

Appendix C – Nonlinear model

This section presents the outlines for a basic nonlinear model to explain the relationship between earnings surprises and CAR. If we trust the historical data we can construct a sigmoid shaped curve like the following:

$$y = A + B\frac{\left(\tanh\left[\frac{x - x_0}{C}\right] + 1\right)}{2}$$

Where: A = The minimum average CAR from our sample

B = The difference in CAR between the best and the worst performing portfolio

x_0 = The center of transition

C = A scaling parameter for the width of the transition

Figure 8 shows an example of a hyperbolic tangent function fitted to our data

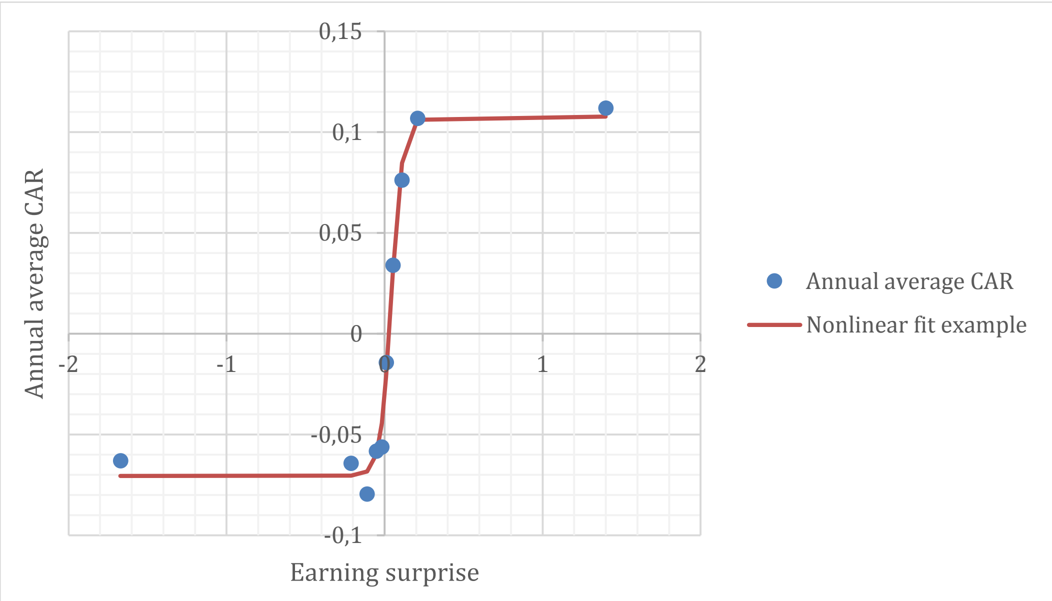

Figure 8 demonstrates that the relation between the earnings surprise and portfolio returns is nonlinear. Any linear function attempting to explain the differences between portfolio CAR will always leave a high unexplained residual variance. The example instead shows how a four parameter hyperbolic tangent function could fit the data.