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The CAP-M Beta-Delta:

An analysis of the importance of macroeconomic announcement days on asset pricing models

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Abstract

The importance of incorporating macroeconomic announcements into asset pricing models is becoming more clear in the academic literature. Evaluating 20 years of stock returns in a sample from 1999 until 2019, this paper applies a novel way of sorting by their beta-delta: a difference between the CAP-M beta of an asset on days that macroeconomic news was scheduled to be announced, and days that no such announcements took place. While no significant differences in returns between all high and low portfolios that were constructed can be reported, several interesting findings shed light on the differences between such portfolios. Portfolios of stocks with larger deltas between those betas incur less market risk, and are less exposed to size factors. Additionally, they incur less negative exposure to momentum, and are more positively associated with profitability factors. Next to these findings, ample suggestions for further research are identified.

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1. Introduction

Over the recent years, the literature on how macroeconomic uncertainty is priced in the cross-section of stock returns has been developing at a rapid pace. Traditional theory, suggesting that solely exposure to the market portfolio and an individual stocks' exposure to it should determine results, can be considered as long outdated. At the very least, other important indicators have been identified, whose robustness has stood the test of time to date. Important examples like the size and value factor, identified as early as the 1930s[1], culminated into one of the most well-known multi-factor models regarding asset pricing: the Fama & French three-factor model (1993). The development of other factors over time has been, resulting in additional explanatory phenomena like momentum[2] and the publication of a five-factor model including the profitability and investment factors (Fama & French, 2015). These factors are a good starting point to describe the theoretical basis upon which this thesis is built.

Secondly, the importance of macroeconomic uncertainty in the cross-section of asset returns has found its way into the literature more and more. Many authors[3] find, that in periods of higher uncertainty, investors want to be compensated for additional risk sustained from being exposed to risky assets in an uncertain time. These findings are interesting, as they shed new light on asset pricing models and deem it important for them to incorporate the state of the economy or uncertainty. Such results are found not only in the cross-section of equities, but even in bond, option, and currency markets. If such results are true, and uncertainty-averse investors want to be compensated for having assets in their portfolio during these times, the assets themselves also become an important factor in the equation. Not every asset responds to uncertainty in the same manner, as Bali et al. (2017) demonstrate. And therefore asset pricing models as described above might not apply to all assets in the same manner. Additional to that, is that they are not continuous over time.

More specifically, Savor & Wilson (2014), show that the relationship between excess return and the CAP-M beta, the simplest of asset pricing models, is very different for scheduled announcement days of macroeconomic news, compared to days when no news is scheduled to be announced. This finding implies that asset pricing models are more effectively at determining prices on announcement days, while the relation on non-announcement days, which may lead one to question the validity of such models when run over all trading days.

[1] E.g. in Graham, Dodd, and Cottle's (1934) book security analysis.
[2] See, for example, Carhart (1997)
[3] See, for example, Bali et al. (2017), Ang et al., (2006), Baltussen et al. (2018)

On top of that finding, surprises in macroeconomic announcements may affect the impact of these announcements have on the market (Beber et al., 2015). This is where the literature on both topic comes together, and the research field for this thesis is formed. In their paper (2015), Beber et al. propose a methodology that aggregates a battery of surprises in macroeconomic news announcements into an index that is able to explain future economic conditions. Uncertainty being one of them, such an index could be utilized to interpret uncertainty at points in time, while being only reliable on (macro)economic data instead of deriving it from the performance of assets.

As presented before, much research is done into how the returns of assets behave on announcement days, hereafter called A-Days, as compared to N-Days, and when I refer to the A-Day and N-Day betas, they are the CAP-M betas that are run over the different windows of either announcement or non-announcement days, respectively, with the delta being the difference between the two for any point in time. In the literature, this has been done separately so far. On the contrary, just as it is relevant to determine whether assets are sensitive to economic uncertainty, I deem it important to look into the difference in behaviour of asset returns on A-Days and N-Days for each asset specifically. Such a difference can be computed using a simple methodology ending up in creating differences in A-Day and N-Day betas for each stock individually. More specifically, I will investigate what influence the difference between these betas over time has on the cross-section of US stock returns between 1997 and 2019. By constructing indicators for how sensitive individual stocks are towards uncertainty by comparing their announcement-day and non-announcement-day betas, portfolios are then created to test whether such stocks underperform compared to less sensitive stocks.

All of the above then synthesizes in the following research question for this thesis:

What is the influence of the difference between announcement day betas and non-announcement day betas on the performance of stocks over time, in terms of return, volatility, and exposure to investment factors?

By measuring A-Day and N-Day betas over rolling windows of varying length, deltas in these betas can be defined for each stock individually. The portfolios will be created on the basis of these differentials. The performance of these portfolios, most importantly the top and bottom ones, will be evaluated. Thereafter, multi-factor model regressions will be run on several top and bottom portfolios in order to test their exposure to these factors and determine the differences between the stocks with the highest beta-delta and the lowest. Additionally, I will test whether surprises in these macroeconomic announcements, through creating a surprise index over time, can be a possible explanatory factor of the returns of the portfolios with the largest and smallest beta-delta.

Based on the literature, the higher this beta-delta, the more sensitive the stock is to economy-wide uncertainty, as its return behaves differently on days when important macroeconomic news is announced. Within the theoretical framework of this thesis, investors are assumed to want more compensation for holding such stocks with higher uncertainty. Therefore, the main hypothesis of this thesis is as follows:

Stocks with the highest beta-deltas are expected to underperform compared to stocks with the lowest beta-delta in terms of return.

In the analyses, no statistical support can be found for the hypothesis that stocks with a low beta-delta outperform stocks with a high delta in terms of return, when correcting for beta itself. More to the contrary, the bottom portfolios usually perform equally well or worse. In the univariate sorts, portfolios of stocks with a higher beta-delta actually outperformed the portfolios with a lower delta. These results might be noisy, as univariately sorting automatically sorts the stocks of higher beta in the top portfolios to begin with. Evidence for the hypothesis that surprises in these announcements have explanatory power in portfolios with high or low beta-deltas can neither be provided. The following main findings can be confirmed.

Firstly, sorting for beta-delta leads to the fact that portfolios with a high beta-delta have lower volatility compared to the ones with a low beta-delta. This result is robust to many specifications, including the selection of announcement days (the top 4 or 10) and the length of the rolling window which is used to calculate the betas (60 or 252). While volatility is often looked over in academic literature, the practical implications of this finding are potentially large, as many investors often seek to minimize variance in their portfolios next to maximizing returns. More on this follows in the discussion section.

Secondly, some differences in factor-characteristics can be identified between portfolios with the largest beta-deltas compared to the ones with the smallest. Firstly, portfolios with large differences in beta-delta appear to be less sensitive to market returns. Whereas portfolios with small beta-deltas have a high exposure to the size factor, this effect is nearly halved for their counterparts. Portfolios with higher beta-delta are more exposed to the profitability factor, with the equal-weighted portfolios even switching signs (the low ones being negatively exposed).

Lastly, the negative exposure of momentum is much less in the portfolios containing stocks that have large differences in betas.

While the implications and limitations of these findings will be discussed at the end of this paper, the limitations to the research performed in this paper can certainly not be overlooked. I deem it important to note that although the research question to this paper has to remain largely unanswered, this does not mean that no relation in terms of returns and beta-delta exist. Possible explanations for this, including suggestions for further research, are presented in the discussion section.

This research adds to the academic literature as it is, to my knowledge, the first study to sort assets based on a within-stock beta differential. It extends the literature on the importance of scheduled announcement days, in combination with the surprise those contain. Therefore, the results are a first indication whether such a sort yields different results in terms of return, volatility, or exposure to certain factors. Its practical relevance can be for anyone with an interest in investing. Firstly, larger (institutional) investors who are able to work with enough capital to engage in factor investing might have an interest in the results obtained. To such investors, this thesis sheds light on the exposure to the different factors for portfolios with either high or low beta-delta. More generally, it is undeniable we live in a world where information reaches people much faster compared to, for example, a time before the internet and social media. Facts like these could make the importance of research into the topic of macroeconomic announcements and their relation to stock returns even larger.

2. Literature review:

The entire literature on asset pricing models is vast. This literature review will start with reviewing only the most relevant literature to this paper. Starting with the earliest and simplest of asset pricing models like CAP-M (Sharpe, 1964, and many thereafter) to models that incorporate not only factors that contain characteristics of the assets themselves (Fama & French, 1993, 1995) but also (macroeconomic news) variables that represent the state of the economy as a whole. Additionally, surprises in the announcements of such variables, defined as the difference between the expected announcement (drawn from a consensus of forecasts' by economists) can be used to create an index of surprises (Beber et al., 2015). Such an index could then be used to predict future stock returns (Baltussen & Soebhag, 2022).

While previous literature in asset pricing has mostly only been incorporating such factors drawn from the performance of assets as relevant predictors for performance of a variety of assets, the combination of all these inputs into an asset pricing model in the end leads to an as complete as possible analysis, minimizing residuals / IVOL overall. While I only attempt to make a slight contribution towards such a model in the future, I deem it important to account for all these areas in this review, albeit briefly. As of recent years, the importance of the macroeconomic news flow (in one way or another) in asset pricing models has been demonstrated numerous times (Bali et al., 2017) (Savor & Wilson, 2014), and this paper can be considered a direct elaboration on such research. Therefore, I will start by touching upon the literature describing what such macroeconomic news is and why it is relevant, how to incorporate it into an index, and potentially a pricing model. Then, I will describe the literature that goes into the significance of the days that macroeconomic news is announced, hereafter called A-Days (and N-Days for trading days in which no announcement has been made).

2.1 Uncertainty & macroeconomic news announcements

The research that has been done on the effect changes in macroeconomic variables has been abundant and growing rapidly over the past fifteen to twenty years. Having these variables or shcoks proxy for uncertainty at a certain point in time appears to be very relevant. However, uncertainty does not always find its origin in macroeconomic variables. For example, Bloom, 2009, investigates major uncertainty shocks (that would appear for example following the assassination of a president, the Cuban Missile crisis, or a terrorist attack), and finds that such events cause rapid recessions in terms of output, employment and productivity. This is then followed by an overshoot in those three variables, following in a swift manner.

Jurado, Ludvigson, and Ng (2015) find that when uncertainty in the market is proxied by macroeconomic activity, estimates for uncertainty become more robust in terms of being able to predict asset prices when expectations of market participants are taken into account. Their model incorporates expectations of macroeconomic news announcements, and the dispersion from their actual value. Such a feature is deemed important as it actively incorporates what the uncertainty was at a point in real time when such an expectation is published.

A similar approach is followed by Beber et al. (2015), extracting daily factors on announcements in four different areas: sentiment, employment, inflation, and output. They incorporate the forecasts of a panel of economists from two to one week in advance into their model as well. Important to point out, is that these forecasts can be adjusted at any time during the week that they are not set yet (up until a week ahead of the announcement itself), and so represent a real-time expectation, but also a possible change in expectation, of the macroeconomic news flow. Such a method will also be used in this thesis, to attempt to provide a surprise index which is robust over time and accurately represents beliefs in real time. Taking into account such beliefs in asset pricing models over time is important for a couple of reasons.

First of all, Drechsler (2013) finds that a representative investor's choices when constructing a portfolio, especially when selecting index options, are in line with concerns he might have for the misspecification of the pricing model. His model also incorporates an uncertainty factor over time. This importance of ambiguity being a factor influencing investors' decisions when it comes to selecting assets for their portfolio, at least in equities, is especially relevant to this paper as it presents a research opportunity that perfectly matches the fields of asset pricing and behavioural economics.

Building upon that, Antoniou, Harris and Zhang, (2015), find that in periods of higher ambiguity in the markets, participation in equity funds decreases significantly. More importantly, their research focuses on probabilities of investing by average households. With an increase in retail investors in financial markets in the US, especially since the outbreak of the COVID-19 pandemic (Pagano et al. (2021), these findings become increasingly significant. Pagano et al. (2021) demonstrate, using user activity data from the popular trading application Robinhood, that such retail investors actively engage in what could be considered biased (momentum, for example) strategies and demonstrate herd behaviour in periods that market conditions are shifting.

2.2 Announcement days and Beta

As described in the previous section, the support in the literature for the significance of announcements, their surprise, and ambiguity/uncertainty in the market is most relevant when pricing stocks. An important next step is then to determine what effect this has on the asset pricing models currently employed. This section will dive into the various literature supporting alternative takes on an asset pricing model that is continuous across all trading days.

The common lesson in corporate finance that the return of a stock is determined solely by the market return, a risk free rate and its exposure to the market return has been outdated for a long time now. Although many additional factors, like size, book-to-market (Fama & French, 1993), profitability, investment (Fama & French, 2015), momentum (Jegadeesh & Titman, 1993), short-term reversal, liquidity (Nagel, 2012) are commonly accepted as relevant in the cross-section of stock returns, many authors feel that simply a more extensive model is not enough. Many studies show, that the return of stocks, at least in the US, do not behave the same across all trading days. Days where the Federal Open Market Committee (FOMC) has scheduled to announce monetary policy are, by now, widely considered as relevant days where the majority of the returns of asset prices can be attributed to (e.g. Savor & Wilson, 2013, 2014, 2016). One shouldn't forget, however, that many other institutions provide announcements on the state of the macroeconomy, even though they receive less attention in the academic literature. Most findings on the significance of announcement days is robust across asset classes time. This section will touch upon the most relevant findings of the literature on that subject.

Not only announcement days themselves are significant, the FOMC Cycle is highly relevant for equity premiums in the US (Cieslak, Morse & Vissing-Jorgensen, 2019). The FOMC meets eight times a year, or every six weeks, and so one period of roughly six weeks from meeting to meeting is called a cycle. In their research (2019), with data spanning from 1994 until 2016, the authors find that returns are for a large extent attributable to weeks 0, 2, 4, and 6 of the cycle. Intermeeting target changes are usually presented in even weeks, and the authors conclude that both announcements and especially informal information in the form of leaks on (changing) monetary policy that is to be implemented find their way to the markets. Returns are much more defined on those periods in time, in a systematic fashion.

The Fed is, though, aware of the reaction to their policy changes. Since 2011, press conferences are held by the chairman of the Fed after the announcements, but only for half of them. Boguth, Grégoire & Martineau (2019) suggest quite implicitly that more important news is communicated in announcements that are followed by a press conference (although this is not confirmed in any fashion by the Fed itself). They (Boguth et al., 2019) find that this causes investor attention to then be skewed towards announcements that are followed by a press conference, and so leaving the other half deemed as less important. This is an important finding, once again highlighting the limited attention investors have (previously shown by amongst others Hirschleifer et al., (2011), Peng & Xiong (2006)) potentially resulting in biases or partial intake of information.

However, there are more announcements regarding macroeconomic shifts than just monetary policy announcements by the FOMC. The importance of announcements on unemployment news, for example, has previously been well documented by Boyd, Hu & Jagannathan (2005). They find that an announcement in the increase of unemployment is not unidirectional. During economics recessions, stock returns tend to benefit from rising unemployment, while this relationship is reversed for expanding periods in the economy.

Responses to announcements regarding inflation have are well documented and robust over time as well. Pearce and Roley (1985) found that the unexpected component of such announcements is significant for stock prices, although the evidence for inflation surprises is considered weak.

Highlighting the importance of announcement days, Savor & Wilson (2013) extend the set of days that are relevant to include more than just FOMC announcements. Additionally, price and output indices, as well as employment figures are included in the set of announcement days, and they conclude that over 60% of the cumulative return of the equity risk premium is earned on such days, while they only account for 13% of trading days. Another important finding of theirs (2013), is the fact that the level of uncertainty in the economy is directly significant on the differential between returns on A-Days and N-Days.

Taking announcements from these four categories, namely output, inflation, employment and sentiment, a robust set of announcement days can be created for which the CAP-M holds and increases in beta correspond with increases in return (Savor & Wilson, 2015). Their results are robust when controlling for beta itself, industry effects, as well as several test portfolios sorted by value or size. Additionally the same relation holds for other asset classes, like bonds and currencies, amplifying the importance of these announcement days even more.

3. Data & Methodology:

In this section, the methodology towards both obtaining data and creating the variables used in all analysis is described. All models are portrayed, and explained, and the reasoning for selection of each one is used given. I start by explaining the macroeconomic announcements that are relevant to this paper. Then, the process of creating daily A-Day and N-Day betas is described. After that, the creation of the surprise index, using the same announcements as previously described, is portrayed. This section closes with the different models that are used in the regression analyses on the portfolio return series once sorting is complete. It is important to mention here, that throughout the entirety of this paper risk-free rates and transaction costs have been left out of the equation. In the discussion, I will get back to why this is and what implications this has for the obtained results.

3.1 The macroeconomic announcements

In this paper, a total of 59 macroeconomic news announcements and their forecasts are taken into account. All announcements are made publicly available, and so all market participants could become aware of their release if they so desire. Firstly, the top 4 and 10 announcements sorted by relevance[4] and their announcement days have been isolated and will be used to construct the rolling betas. In a later section in this paper, all announcements will be used to create a macroeconomic surprise index. These announcements and their forecast are drawn from a panel of market participants, usually economists, and are collected by the Bloomberg Economic Calendar (ECO) (McCoy et al., 2020). A key feature of the forecasts is that they can be adapted for a week: they can be submitted one to two weeks ahead of the announcement and after that the announcement is no longer changable (McCoy et al., 2020). Therefore, I assume that when these forecasts are set, they represent the actual beliefs of the panel members including their updated beliefs on any events that occurred up until a week before the announcement. Therefore, for each observation, true surprise at that point in time is measured by taking the difference between the forecasted value and the actual announcement.

A complete overview of all announcements can be found in appendix C. As the top four announcements are highly relevant to the main results of this paper, each one will be discussed here briefly. Table 1 presents an overview of the ten variables. All variables from the top four are measured from at least 1998 onwards, with the complete top ten being available from 2001 onwards. All announcements have a relevance index of at least 91, while at least 94% of Bloomberg users are notified by each announcement in the top four.

In the top four, starting with the output announcement; the GDP Annualized QoQ. It measures the annualized change in inflation-adjusted value of final goods and services in the United States and is released by the Bureau of Economic Analysis of the United States. (Bureau of Economic Analysis, 2021). It reflects the state of the economy of the USA and is the most popular indicator on that subject (Bureau of Economic Analysis, 2021). Secondly, the Change in Nonfarm payrolls is released by the US Bureau of Labor Statistics, and measures the change in employment for all sectors other than farm workers and a very small set of other occupations (Bureau of Labor Statistics, 2022). It is released once a month in their Employment Situation report, together with the unemployment rate (Bureau of Labor Statistics, 2022). Additionally, the monthly change is presented on their website and publicly available. It is widely considered the most important indicator on employment in the United States. Then, the Conference Board of the US presents a consumer confidence index in their monthly report. It *"reflects prevailing business conditions and likely developments for the months ahead*" (US Consumer Confidence, 2022). It is an important representation in this dataset because it represents views of consumers, a very broad and diverse set of market participants. Lastly, the CPI MoM is also presented by

[4] This relevance index is constructed by taking the percentage of users of the Bloomberg terminal that set up an alert to be automatically informed when the respective announcement was released (McCoy et al. (2020))

the US Bureau of Labor Statics. It “measures inflation derived from the prices of both goods and services, but from the perspective of the consumer” (Bureau of Labor Statistics, 2022). Similarly to the consumer confidence index, it therefore captures inflation as interpreted by a wide and diverse audience throughout the US.

Table 1

This table presents the top 10 announcements based on their relevance index as presented by the Bloomberg Economic Outlook. The announcements are sorted fistly by whether they are the most relevant in their category. The 4 most relevant announcements per category are depicted in Panel A, with the others ones in Panel B. Within each panel, they are sorted chronologically by release date.

Announcement	Frequency	Category	First observation	Relevance
Panel A: Top 4 announcements				
GDP Annualized QoQ	Monthly	Output	1997	97
Change in Nonfarm payrolls	Monthly	Employment	1997	99
Conf. Board consumer confidence	Monthly	Sentiment	1997	94
CPI MoM	Monthly	Inflation	1998	96
Panel B: Remaining 6				
ISM Manufacturing	Monthly	Output	1996	95
Initial jobless claims	Weekly	Employment	1997	98
New home sales	Monthly	Output	1997	91
Durable goods orders	Monthly	Output	1997	93
U. of Mich. Sentiment	Twice a month	Sentiment	1999	94
Retail Sales Advance MoM	Monthly	Output	2001	92

Creating rolling A-Day and N-Day betas over daily stock data and merging only monthly data

In order to obtain the A-Day betas and N-Day betas, daily stock data of the three main US exchanges (NYSE, Amex, Nasdaq)[5] has been collected. I have selected all common stock (stock type 10 and 11) from the merged CRSP / Compustat database. In order to make the sample, a stock needs to have at least 60 consecutive trading days of observations present at any given time. A value weighted market return is constructed as follows. For each day in the sample, every stock that has a return on that day is weighted by its market capitalization relative

[5] Following the methodogy of a.o. Savor & Wilson (2014), this allows for a universe of equities that is most tradable and therefore an apt representation of a liquid set of assets.

to the entire capitalization on that day. The return of each stock is then scaled by that weight in order to obtain the market return throughout the sample.

Next, the sample is divided between A-Days and N-Days in two different ways. Primarily, the top 4 announcement days are used to create a subsample of trading days that consist of 1070 trading days over the entire sample, which runs from 1997 until and including 2019. With 6040 trading days in total, this entails that roughly 18% of all trading days are then considered A-Days. Secondly, the top 10 announcements are used to create another set of trading days. Because of the weekly and bi-monthly occurrence of Initial Jobless Claims and U. of Mich. Sentiment respectively, a substantial increase in trading days (2940) now means that sample is split roughly in two (49% A-Days and 51% N-Days). Next, simple market betas for every equity i are calculated for each specification for both A-Days and N-Days, following model 1.

$$\beta_{roll_i} = \frac{Cov(i,mrkt)}{Var(i)} \tag{1}$$

A couple of specifications are run: obtaining four different sets of betas. More specifically, each specification of A-Days (and its respective N-Days), is run over both a 60 and 252-trading day window. The reason for running 60 trading day windows, is to capture the timing of macroeconomic surprises in beta cross-sectionally. 252-day windows are more robust betas.

Then, the last A-Day beta and N-Day beta in each month for each stock is retained. Following such a methodology, I obtain A-Day and N-Day betas for each stock i in every month inside the sample, and deltas for every equity i can be calculated as in model 2. These are the deltas that are used for sorting the stocks later on in this paper, and so form

$$\Delta_{\beta_i} = \left| \beta_{N_i} - \beta_{A_i} \right| \tag{2}$$

In order to obtain reliable returns for the universe of equities all analysis will be run on, I compute a different set of monthly returns comprised of a universe of liquid stocks[6]. This dataset is obtained by sourcing from CRSP and Compustat separately, and merging them together for each asset. This methodology ensures that known anomalies in CRSP data like the delisting bias (Shumway, 1997) are not incurred when calculating return series later, while

[6] Following a methodology of Fama & French (1993, 1995) in which they obtain a liquid, tradable universe upon which their factor models are run.

Compustat data is used to obtain and safeguard accurate book values and market values for each asset in the sample. Ultimately, I obtain a sample of data for all common equities (sharecode 10 and 11) between 1997 and 2019, and retain only those for which a delta between the A-Day beta and N-Day beta is calculated. In the last section of this methodology, all performed analyses and statistical tests will be explained. All inputs to those analyses, unless otherwise stated, are from the universe of stocks described in this section.

3.2 The surprise index

In order to perform tests later in this analysis, a surprise index is created following the simply methodology by McCoy et al. (2020). In their article, the authors propose an index that consists of a moving average (of 1 year, or 8 FOMC meetings) of surprises in news announcements over time[7]. Their index shows that surprises in an activity index alone are able to explain almost 17% of the shifts in the S&P500 index (McCoy et al., 2020). The reason for choosing this methodology in this paper, is that by using a moving average, surprises over time are aggregated to periods of under, or overestimation of announcements in the market. This ensures that the index captures, to a certain degree, uncertainty in the market amongst economists who provide the forecasts, a key feature when using this index in the analysis later on.

To create the index, each trading day is looked at separately. For each day, all surprises in announcements that are made on that day are converted into a datapoint at that day only. If there are multiple announcements made on the same day, an average of all their estimates is used on that day, such that all announcements are equally weighted[8]. The surprise in an announcement is measured by taking the actual value of the announcement and subtracting it with the median of estimates as submitted by the respective panel for that announcement. All announcements are scaled to their own historic standard deviation such to create a mean of zero and standard deviation of one. The datapoints at any given trading day T, for a number of N announcements i on that day and in the sample are thus formulated as in model 3.

$$Surprise_T = \sum_{i=1}^{N} \left(\frac{A_i - M_i}{std(A_i - M_i)} * \frac{1}{N} \right) \qquad (3$$

[7] Their methodology creates an index on a daily frequency, with the surprise on that day being scaled (using the relevance index) to the relative weight of the announcements that occur on that day. (McCoy et al., 2020)

[8] The reason for equally weighting all announcements, contrary to the methodology upon which this paper is based, is because we are purely interested in the macroeconomic surprise. It thus matters less if there the more relevant announcements bear surprises, but rather what the dispersion is within all announcements. This captures uncertainty better in times when surprises are large, both in the negative or positive.

With so many announcements, 4685 (roughly 78%) trading days out of the 6040 have at least one announcement and so a datapoint. Once datapoints for every trading day have been created, it is important to 'fill the gaps' for trading days that do not have a value assigned. Without correcting for these missing values, rolling windows will be created over unbalanced panels and so less accurate. Missing values will be filled with the first surprise value that can be found from any trading day beforehand[9]. Because of the large amount of announcements, this delta is very rarely larger than 2 trading days. Table 2 provides a visualization of that process, using a hypothetical situation in which three out of six trading days would have obtained datapoints.

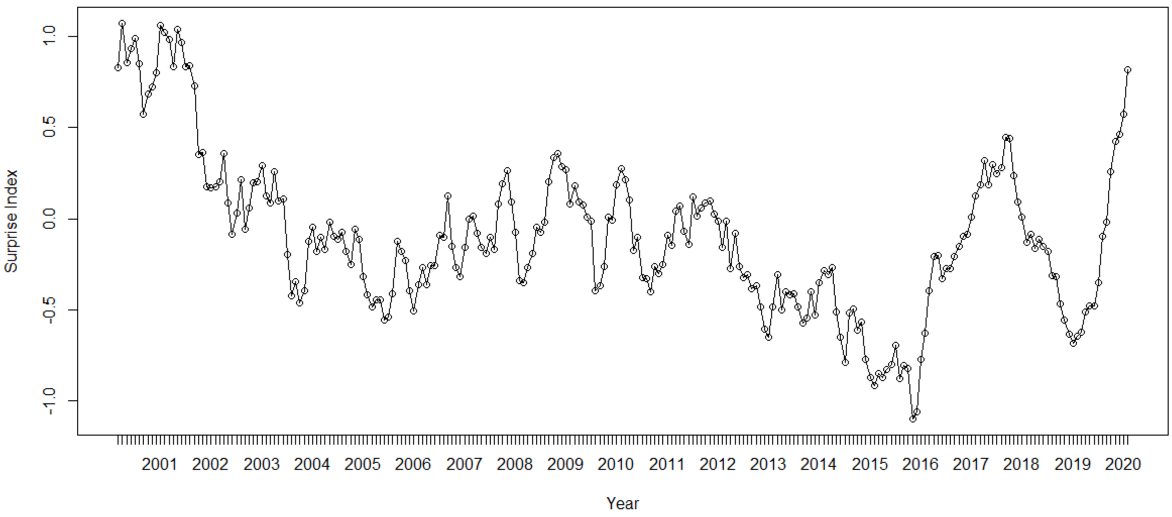
Table 2
Methodology for filling missing values
A visualisation of the method used to make the index continuous across trading days. Column 1 represents a hypothetical example of the output from computing the datapoints at each trading day on which announcements are present. Column 2 then represents the way all days t until t +5 would be filled with the values from the observation prior to the one with a missing value.

	(1)	(2)
T_t	S_t	S_t
T_{t+1}	No value	S_t
T_{t+2}	No value	S_t
T_{t+3}	S_{t+3}	S_{t+3}
T_{t+4}	No value	S_{t+3}
T_{t+5}	S_{t+5}	S_{t+5}

Once datapoints have been generated for all trading days within the sample, a simple moving average of 252 trading days is drawn to create the surprise index itself. The incorporation of the index in asset pricing tests will follow in the next section of this methodology. Figure 1 below already represents the index over time. Most noticeable is the relatively high level of surprises in forecast at the beginning of the sample, until 2002. The most negative surprises are realized in the period from 2012 leading up to 2016, rapidly increasing thereafter. Additionally, peaks around mid-2018 and leading up to the end of the sample at the end of 2019 stand out.

[9] A similar methodology is used in Beber et al. (2013), which also tackles missing values at a certain point in time this way.

Figure 1: The surprise index



3.3 Variable definitions

In order to test differences between the portfolios I create, two main statistics are being analysed later. Firstly, it is important to see if, by sorting for beta-delta, positive alphas can be generated for any of the portfolios created. Secondly, multi-factor models will be run over the portfolio returns so determine the exposure to, if any, factors that are generated by sorting by beta-delta. Lastly, the surprise index will be used as a factor to see whether that has any explanatory power on (any) of the portfolios.

An overview of the models and the variables within will be described in this section. All models that are mentioned here will be ran later in this paper for various return series. The exact specifications used in the analysis are discussed in the results section, whereas here I focus purely on describing the models and their variables as used later on. All models described here are run on a monthly frequency. To start with, model 4 only includes a market factor, which is value weighted or equal weighted depending on the specification of the models run.

$$R_i = \alpha_i + \beta_i^{Mkt} R_{Mkt} + \epsilon_i \tag{4}$$

Then, for model 5, the Fama & French (1993) three factor model is used to measure exposure to the value and growth factors. Being one of the most widely accepted models in the factor analysis literature, I deem it important to check whether positive alpha can be generated when running such a model. Additionally, controlling for a value factor is most relevant as the value weighted returns are created on a monthly basis. These factors have been obtained from Kenneth French' website.

$$R_i = \alpha_i + \beta_i^{Mkt} R_{Mkt} + \beta_i^{SMB}(SMB) + \beta_i^{HML}(HML) + \epsilon_i \quad (5)$$

Model 6 includes three additional factors, ones that have been prominent in the literature since significantly later, but have gained serious attention in financial literature only over the past decade and a half. The first two are Fama & French' (2015) profitability (RMW) and investment (CMA) factor. Additionally, and perhaps most importantly, following Carhart's (1997) methodology a momentum factor is included.[10] Next to the fact that a momentum factor has been widely accepted since the early 90s, it is especially important to include it as a factor in this research. The reason for that is the methodology of measuring beta, which is very time-sensitive when using relatively short windows like 60 and 252 trading days. Checking for exposure for momentum therefore could be deemed a must, which completes the last model.

$$R_i = \alpha_i + \beta_i^{Mkt} R_{Mkt} + \beta_i^{SMB}(SMB) + \beta_i^{HML}(HML) + \beta_i^{RMW}(RMW) + \beta_i^{CMA}(CMA) + \beta_i^{Mom}(Mom) + \epsilon_i \quad (6)$$

Lastly, model 7 will be run in order to determine whether the surprise index has any explanatory power over the return of these portfolios that are created[11]. It will be applied to both the top and bottom portfolio, using the following equation:

$$R_i = \alpha_i + \beta_i^{Surprise}(Surprise_{Index}) + \epsilon_i \quad (7)$$

[10] All factors have been extracted from Kenneth French' website.

[11] Following the methodology of McCoy et al. (2020), who find significant coefficients for their surprise index when regressed on the S&P500 returns, concluding macroeconomic surprises are to some extent able to explain returns of such an index.

4. Empirical results

This section presents the results obtained from all analyses performed for this paper. In this section, I aim to only portray the results as they were found, with the interpretation of them following in the discussion section. There, the limitations to both the methodology and the findings of them will also be discussed. This section starts by presenting the results from the univariate analysis. Then, bivariate sorts will be discussed, followed by the multi-factor model regressions performed on the resulting portfolios that are created. Lastly, one-Dollar investment simulations are run on two portfolios and the return series over the entire sample are discussed.

4.1 Returns on the entire universe of stocks created

Table 3
Returns and volatility of the market portfolios
In this table, returns for portfolios are created when all stocks that made the sample are included. Column 1 presents the value weighted return, standard deviation (both have been annualized) and Sharpe ratio, while column two contains the equal weighted alternative.

	(1)	(2)
Return	0.0782	0.1239
Standard deviation	0.1477	0.2017
Sharpe ratio	0.53	0.61

Firstly, the returns on the entire market portfolio are calculated. To determine whether significant alphas can be generated when stocks will be sorted in portfolios based on their beta-delta, it is important to firstly describe the would-be returns on the entire market. The return on a value weighted index of all stocks present in this sample, when using the 4 announcement days by 60 trading day rolling window, is 7.82% on an annual basis, with a standard deviation of 0.1477. The return on an equal weighted portfolio is higher, at 12.39% annually, but the standard deviation increases as well, which sits at 0.2017.

4.2 Univariate sorts:

Firstly, decile portfolios are created based using the beta-delta to sort stocks into each decile. Each decile contains exactly 1/10th of the amount of equities that is present in the sample at each month they are formed. The portfolios are rebalanced monthly, ensuring that the equities with the largest beta-delta in one month are always sorted in the top portfolio the month thereafter, and vice versa for the smallest. Here presented, as the main results, are the return series for using the top 4 announcements as A-Days, over 60 day rolling windows. In appendix A, a battery of other specifications that have previously been discussed is presented, all yielding similar results. The discussion on these will follow later in this paper.

For each return series, mean A- and N-Day betas are calculated and presented. One will immediately notice that by sorting for the largest difference, the equities with the largest rolling betas are sorted towards to top of the deciles. This phenomenon can easily be explained, as differences are relatively small overall anyway, so stocks that have higher betas easily compute larger differences for the beta-delta. Looking at the return series for the value weighted portfolios, it becomes apparent that sorting for this difference univariately does not significantly yield portfolios of higher returns. Although the top portfolios tend to outperform the bottom portfolios, this is the less interesting find. Much more interestingly, is the way the volatility of the return series is distributed amongst the portfolios. For both the value and equal weighted portfolios, volatility declines steadily and in a constant fashion as you move up the deciles. These results present a first indication towards the fact that sorting for beta-delta does not yield higher retains per se, but could indeed decrease the volatility of portfolios.

This finding is somewhat confirmed by the alphas generated when running the three factor models on the return series. For model 4 and 5, statistically significant positive alphas (up until the .01% level) are generated for the top deciles. And more insignificant alphas are generally found towards the lower end of the portfolios. Once accounting for the three additional factors, however, no relation between alpha and moving up the deciles can be concluded at all.

All of these results are confirmed in the equal weighted portfolios. As returns in those portfolios are not corrected for their market capitalization, returns are even more homogeneously distributed amongst all portfolios, confirming the earlier expectation.

Table 4

Univariate sorts

This table presents the results of creating decile portfolios when sorting for beta-delta. The top portfolio contains the stocks with the largest beta-delta at the beginning of each month. Portfolios are rebalanced monthly. Column 1 and 2 present the mean A-Beta and N-Beta in each portfolio respectively. Column 3 presents the annualized return of each portfolio, with the annualized standard deviation in parentheses. Column 4 presents the Sharpe ratio of each portfolio. Lastly, columns 5, 6, and 7 present the alphas (as an annual percentage) generated when the return series of each portfolio are regressed on model 4, 5, and 6 as described in the methodology section. T-Statistics can be found in parentheses. Panel A contains all value weighted returns, while panel B presents the equal weighted variants.. The sample period was 1999-2019

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Panel A							
Top	0.27	0.25	0.1180 (0.1378)	0.86	0.49 (3.213)**	0.41 (3.317)**	0.18 (1.553)
9	0.22	0.20	0.1124 (0.1673)	0.67	0.37 (1.994)*	0.26 (1.747)	0.18 (1.181)
8	0.19	0.18	0.1387 (0.1939)	0.72	0.49 (2.362)*	0.35 (2.146)*	0.26 (1.592)
7	0.17	0.16	0.1321 (0.2053)	0.64	0.46 (1.908)	0.35 (1.597)	0.04 (2.032)*
6	0.15	0.14	0.1167 (0.2359)	0.49	0.32 (1.1)	0.17 (0.678)	0.34 (1.379)
5	0.13	0.13	0.1375 (0.2263)	0.61	0.51 (1.763)	0.36 (1.480)	0.51 (2.015)*
4	0.12	0.12	0.0774 (0.2430)	0.32	0.05 (0.164)	-0.07 (-0.251)	0.15 (0.497)
3	0.11	0.11	0.0499 (0.2552)	0.20	-0.26 (-0.856)	-0.34 (-1.176)	-0.07 (-0.227)
2	0.11	0.11	0.1105 (0.2500)	0.44	0.30 (0.904)	0.14 (0.488)	0.34 (1.166)
Bottom	0.10	0.10	0.0534 (0.3014)	0.18	-0.15 (-0.350)	-0.31 (-0.812)	0.01 (0.029)
Panel B							
Top	0.27	0.25	0.1223 (0.1299)	0.94	0.42 (3.187)**	0.40 (3.438)***	0.03 (0.262)
9	0.22	0.20	0.1226 (0.1620)	0.76	0.21 (2.083)*	0.19 (2.086)*	-0.04 (-0.421)
8	0.19	0.18	0.1235 (0.1806)	0.68	0.11 (1.513)	0.10 (1.423)	-0.04 (-0.547)
7	0.17	0.16	0.1249 (0.1964)	0.64	0.04 (0.754)	0.04 (0.681)	0.00 (0.039)
6	0.15	0.14	0.1232 (0.2102)	0.59	-0.03 (-0.528)	-0.02 (0.473)	0.01 (0.207)
5	0.13	0.13	0.1150 (0.2240)	0.51	-0.14 (-2.22)*	-0.13 (-2.154)*	-0.06 (-0.859)
4	0.12	0.12	0.1145 (0.2355)	0.49	-0.18 (-2.388)*	-0.17 (-2.343)*	-0.02 (-0.280)
3	0.11	0.11	0.1284 (0.2399)	0.54	-0.09 (-1.015)	-0.08 (-0.905)	0.03 (0.401)
2	0.11	0.11	0.1202 (0.2427)	0.50	-0.15 (-1.551)	-0.14 (-1.449)	0.04 (0.450)
Bottom	0.10	0.10	0.1236 (0.2594)	0.48	-0.18 (-1.496)	-0.16 (-1.395)	0.03 (0.276)

Significance levels: *** (0.001), ** (0.01), * (0.05)

4.3 Bivariate sorts

Because this hypothesis of this thesis is unrelated to beta itself, univariately sorting might provide some useful first insights, but are not the results any conclusions can be drawn from. The relation between excess return and beta has long been discussed in the literature[12], this relationship is simply not in scope for the purpose of our hypothesis. Therefore, to examine the true effects of the beta-delta without taking actual beta, albeit A-Day or N-Day, into account, 5x5 bivariate sorts are run. I firstly sort all equities in 5 quintiles. This is done for both the A-Day betas and the N-Day betas. Then, within these quintiles, all stocks are sorted into 5 portfolios based on their beta-delta. All top portfolios from the first quintiles are then used to create a top portfolio of the highest beta-deltas, whereas the A-Day betas and N-Day betas are distributed evenly across all 5 final portfolios. Similarly to before, all portfolios are rebalanced monthly and formed on individual stock characteristics.

These portfolios confirm the findings presented in the previous section. In terms of returns, no significant differences across portfolios can be identified, although in terms of simple returns, no top portfolio performs significantly worse compared to the bottom ones. Although two alphas are statistically significant at the 5% level, no structural relationship between an increase or decrease in beta-delta can be observed. One result that remains robust after controlling for both A-Day and N-day beta is the decrease in variation as the beta-delta gets larger. One notices immediately (and I realize this is not as statistically sound), the variance of all four top portfolios across A- and N-Day sorts and equal or value weighted, ranges only from 0.1477 to 0.1509, remaining within a window of 0.0032 volatility on an annual basis. A similar observation can be made for the volatility of all bottom portfolios, which are significantly higher throughout all samples. These findings confirm the earlier suggestion that beta-delta sorting not so much impacts returns, but all the more volatility. The next section will focus on the regression of these portfolios in order to determine the differences in exposure to the different factors.

This analysis is subsequently also performed in an identical fashion, only with betas rolled over the top 10 announcement days, instead of the top 4. Even though, as previously described, this sample accounts for nearly half of the trading days, significant decreases in volatility are achieved by sorting by beta-delta. Additionally, when the rolling window is increased to 252 trading days, results remain the same.

[12] Starting from early papers e.g. Sharpe (1964), Merton (1973), and Banz (1981) up until more recent papers as Bali et al (2017), the direction of the relationship between an assets beta and excess return is often up for discussion.

Table 5
Bivariate sorts
Each panel presents both a priori A-Beta sorted and N-beta sorted portfolios, which are subsequently sorted by beta-delta. Panel A contains all value weighted portfolios, whereas the equal weighted ones are presented in panel B. Section (a) for both panels presents the A-Beta sorted portfolios, with the N-Beta sorted portfolios in section (b). For each section, column 1 presents the annualized return on each quintile portfolio, with the annual standard deviation in parentheses. Column 2 then presents the associated Sharpe ratio, with the alphas generated by regressing the return series on model 6 presented in column 3. The T-statistics are reported in the parentheses. The sample period was 1999-2019.

	(a) A-Beta sorted			(b) N-Beta sorted		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Panel A						
Top	0.1076	0.73	0.17 (1.200)	0.1219	0.81	0.24 (1.877)
	(0.1477)			(0.1509)		
4	0.1461	0.76	0.28 (1.531)	0.1572	0.83	0.45 (2.522)*
	(0.2001)			(0.1884)		
3	0.0919	0.44	0.10 (0.548)	0.1278	0.60	0.47 (2.180)*
	(0.2079)			(0.2206)		
2	0.1034	0.44	0.07 (0.309)	0.1089	0.48	0.17 (0.752)
	(0.2333)			(0.2264)		
Bottom	0.1057	0.46	0.10 (0.526)	0.0984	0.43	0.12 (0.547)
	(0.2280)			(0.2314)		
Bottom	0.0039	0.03	-0.07 (-0.316)	-0.0180	-0.12	-0.07 (-0.316)
- Top	(0.1386)			(0.1566)		
Panel B						
Top	0.1264	0.85	0.02 (0.237)	0.1230	0.82	-0.00 (-0.035)
	(0.1493)			(0.1506)		
4	0.1271	0.65	-0.02 (-0.478)	0.1273	0.65	-0.03 (-0.662)
	(0.1949)			(0.1969)		
3	0.1156	0.53	-0.06 (-1.267)	0.1246	0.57	0.03 (0.753)
	(0.2185)			(0.2175)		
2	0.1233	0.54	0.01 (0.158)	0.1192	0.53	-0.03 (-0.535)
	(0.2270)			(0.2244)		
Bottom	0.1283	0.55	0.06 (1.009)	0.1262	0.54	0.02 (0.395)
	(0.2314)			(0.2336)		
Bottom	0.0108	0.10	0.21 (1.875)	0.0116	0.10	0.24 (1.867)
- Top	(0.1122)			(0.1186)		

Significance levels: *** (0.001), ** (0.01), * (0.05)

Lastly, long-short portfolios are created for each of the 4 specifications. In each of these portfolios, I go long in the bottom portfolio, containing the stocks with the least difference in alpha, and short in the top portfolios. The results in table 5 show that none of these portfolios yield any significant alpha at the 5% level. Three of the portfolios yield positive returns, while the N-Beta sorted value-weighted portfolio yields a negative return.

Then, and most crucially, the return series of all these 8 top and bottom portfolios are then regressed against model 6, controlling for the market return and the additional 5 factors. For the bottom portfolios in Panel A, we see highly significant coefficients for the market return, indicating all bottom portfolios are quite exposed to the market risk factor. Three out of four portfolios even have a beta over one, indicating these portfolios are more volatile than the market. For the value weighted portfolios, both the A- and N-Beta sorted variations have a high and positive beta for the size factor as well, indicating these portfolios have significant exposure to the size effect and potentially contain smaller cap stocks. The value factor is not significant for any of the portfolios.

The profitability factor is highly significant and negative for the equal weighted portfolios, while the value weighted portfolios are not significantly exposed to this factor. The investment factor, then, is not significant anywhere, while three out of four portfolios are significantly negatively exposed to the momentum factor. The value weighted portfolios are highly significant, , indicating that these portfolios perform worse when stocks with high exposure to momentum are performing better.

Table 6
Regression results
Coefficients for regressions running model 6 are presented below. Panel A contains the four bottom portfolios, while panel B portrays the top portfolios from the bivariate sorts. Section (a) then displays all equal weighted portfolios, while section (b) contains the output for all value weighted portfolios. Within each section, column 1 contains the portfolios who are a priori sorted by A-Beta, while column 2 contains the ones sorted by N-Beta. Alphas have been annualized.

Panel A				
	(a) Equal weighted		(b) Value weighted	
	(1)	**(2)**	**(1)**	**(2)**
Adj Rsq	**0.986**	**0.985**	**0.815**	**0.747**
Intercept	0.06 (1.009)	0.02 (0.395)	0.10 (0.526)	0.12 (0.547)
Mrkt	1.078 (74.612)***	1.086 (73.500)***	1.065 (20.666)***	0.985 (16.131)***
SMB	-0.02 (-0.840)	0.00 (0.204)	0.75 (11.006)***	0.80 (9.935)***
HML	-0.04 (-1.670)	-0.03 (-1.276)	0.06 (0.650)	0.08 (0.766)
RMW	-0.18 (-7.370)***	-0.19 (-7.299)***	0.11 (1.234)	0.01 (0.139)
CMA	-0.01 (-0.167)	-0.03 (-0.841)	-0.02 (-0.150)	-0.12 (-0.850)
Mom	-0.03 (-2.405)*	-0.01 (-0.798)	-0.25 (-6.740)***	-0.20 (-4.492)***
Panel B				
Adj Rsq	**0.952**	**0.935**	**0.760**	**0.803**
Intercept	0.02 (0.237)	-0.00 (-0.35)	0.17 (1.200)	0.24 (1.877)
Mrkt	0.836 (48.728)***	0.836 (41.605)***	0.805 (21.171)***	0.829 (23.584)***
SMB	-0.04 (-1.553)	-0.06 (-2.002)*	0.38 (7.679)***	0.41 (0.8875)***
HML	0.09 (3.026)**	0.07 (2.107)*	0.08 (1.267)	0.12 (2.057)*
RMW	0.28 (9.518)***	0.30 (8.525)***	0.21 (3.301)**	0.20 (3.422)***
CMA	0.06 (1.464)	0.08 (1.819)	0.12 (1.362)	0.19 (2.328)*
Mom	0.07 (5.056)***	0.04 (2.664)**	-0.07 (-2.529)*	-0.09 (-3.330)**

Significance levels: *** (0.001), ** (0.01), * (0.05)

Quite some differences can be noticed for the top portfolios in the sample. Firstly, and perhaps most interestingly, the market betas are all significant, and lower compared to their counterparts from the bottom portfolios. These portfolios are more robust to shocks in the market return, with all betas between 0.800 and 0.8500. Additionally, the value portfolios are less sensitive to the size factor. Although still significant, their coefficients decrease by almost half. For the N-Day sorted equal weighted portfolio, the size factor is negative and significant. The value factor is significant for three out of four portfolios, with positive coefficients for all. The profitability factor is highly significant for all four portfolios, three out of four being at the 0.001 level. Additionally, the sign switches when moving from the bottom to the top portfolio, indicating these portfolios do perform better when profitable firms perform better. The investment factor is significant only for the N-Day sorted value weighted portfolio, while momentum remains significant for all four portfolios. Negative exposure to momentum decreases by more than half for both the value weighted portfolios, while the sign switches for the equal weighted ones.

Lastly, examining the goodness-of-fit of all models in table 6, a distinction between the equal weighted and value weighted portfolios has to be made. All equal weighted portfolios have an adjusted R^2 of at least 0.935, indicating that at least 93.5% of the variance of these returns can be explained with the factors used in the model. The value weighted ones fit less, with R^2 ranging from 0.747 to 0.815. This can still be interpreted as a model that fits well, with the explanatory variables being able to explain at least roughly 75% of the variation in the returns.

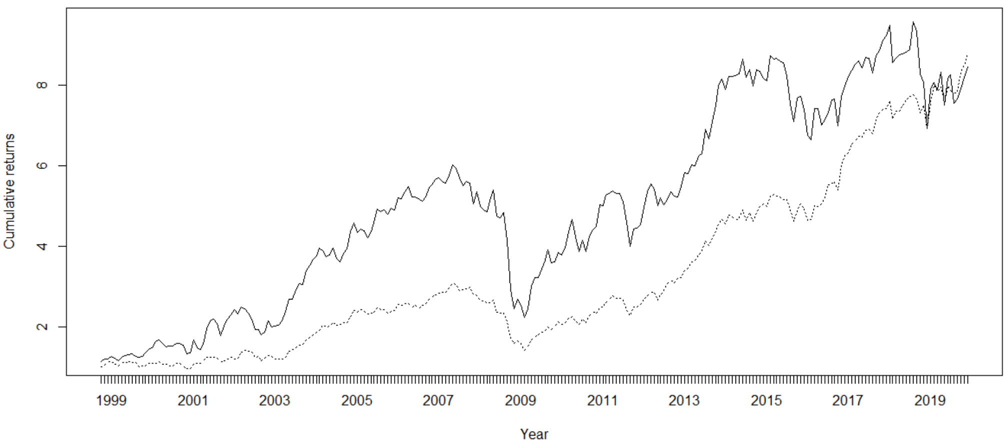
4.4 One dollar investment portfolios

Lastly, to compare both return series, I construct two simulations of 1 dollar investments in both the top value-weighted A-Day portfolio, as well as the bottom value-weighted A-Day portfolio. These return series are then constructed up until the end of the sample, the end of 1999. Both series are presented in figure 2. While both portfolios would yield an investor around 800% return over the entire sample, the difference in variation becomes visible when comparing both graphs. A couple features immediately become noticeable. Firstly, correlation between both return series is quite visible. During the early months in expansionary periods, returns on the bottom portfolio actually grow much faster compared to the top one. This is true for the early months in the post 2003 boom, as well as the recovery period from the global financial crisis after 2009.

Figure 2

One dollar investment return series

This figure portrays the development of a one dollar investment over time of both the top and bottom A-Day sorted value-weighted portfolio. The straight line is the bottom one, while the dotted line represents the top portfolio.



Another interesting feature is the period post 2014. Hereafter, the bottom portfolio downward periods seem to be more persistent when compared to the top portfolio. Meaning correlation in downward periods is less after this point in time. While the bottom portfolio realizes virtually no additional returns past this point, the top portfolio realizes about half of its returns in this period of time.

4.5 Explanatory power of the surprise index

Lastly, model 7 is run to determine the exposure of both this top and bottom portfolio to the surprise index that was created. Unfortunately, these results were statistically insignificant, and as the purpose of this paper is academic, no support for that part of the research can be presented.

5. Discussion

In this discussion, the main findings of this research will be discussed, including their limitations and suggestions for future research. I deem it important to note in advance that no prior research into this beta-delta has been performed, and therefore sometimes specific results are hard to reconcile with previous findings. Especially when evaluating factor loadings, previous research cannot be confirmed or disputed, only new observations made. Thereby comes, that any interaction between macro variables and these factors is not accounted for.

In this analysis, sorting by beta-delta yields significant alphas for a CAP-M and a Fama-French three factor model for the portfolios with the largest delta. This procedure seems to automatically sort stocks of higher beta into top portfolios to begin with, so this result appears to be biased. In order to create an unbiased picture, portfolios are first controlled for both A-Day and N-Day beta, and then sorted into five portfolios. No significant alphas are obtained when constructing the bottom minus short portfolios.

The returns of top portfolios containing stocks with a higher beta-delta are less volatile compared to their bottom counterparts. These results remain robust after changing both the set of A-Days as well as the length of the rolling window the betas were computed in. This finding seems somewhat counterintuitive, as the stocks that have performed the most differently on days news was announced compared to other days, are the most constant in terms of return shocks. Evaluating the return over time in Figure 2, this result seems to only become more robust over time. Since there is no other academic literature comparing A-Day betas with N-

Day betas within stocks, it is hard to reconcile these findings with the current set of literature. This in itself is one of the biggest limitations to this thesis, and provides ample room for further research. On the hand of related literature in the field, some more speculative arguments could be valid as to why this volatility is lower. While this study is the first of its kind, the phenomenon that announcement days account for the majority of returns over time has been demonstrated before[13]. Stocks that perform differently on those types of days compared to days when no news is announced, and thus less uncertainty is present, may perform less volatile over longer period of time because of less reaction to said uncertainty in periods when it is more articulated in the market.

In such a case, the differential between A-Day and N-Day betas might be less relevant, and future research could focus on intertemporal differences with either of these betas. The volatility of these betas over time could very well reflect how the stock reacts to uncertainty over time. Also, if betas remain fairly constant, less uncertainty towards such a specific assets' return can be expected. Additionally, this research did not control for industry effects in any of the portfolios, and thus no conclusions can be drawn as to whether the distribution of these stocks is not skewed due to such effects.

Interestingly, the coefficients of the explanatory variables in the multi-factor models shed more light as to what might explain the returns, and differences in the returns, of the top and bottom portfolios. I start by diving into the fact that portfolios sorted on large beta-deltas have less exposure to the market compared to bottom portfolios. Given that these results are robust to firstly distributing both A-Day and N-Day betas evenly across all platforms, betas of the stocks themselves do not explain this difference. The fact that the returns of those portfolios, over the entire sample, do not appear to be different compared to the bottom ones makes this result even more robust. Comparing the Sharpe ratios between either of the four pairs of portfolios would make a rational investor prefer a portfolio of stocks with a larger difference between A-Day and N-Day beta.

Then, for the both the equal and value-weighted portfolios, exposure to the size factor is less for the top portfolios compared to the bottom. This could imply that companies with higher market cap have larger differences between their A-Day and N-Day betas. What goes for this factor goes for all the next as well; little research has been done on the interaction of these factors with announcement days. The most noticeable difference when comparing coefficients, then, is the increased exposure to profitability. Most recognized in the equal-

[13] E.g. Savor & Wilson (2013) demonstrate that over 60% of cumulative returns is earned on announcement days.

weighted portfolios, the bottom half of the portfolios have significant negative exposure to this factor, whereas the top halves are significantly positively exposed.

A possible interaction between this SMB, RMW and market exposure could be that larger, more profitable companies, incur less uncertainty in their returns. Therefore, on announcement days, where most of the returns are being realized, they might be less sensitive to surprises in such announcements and the market movement this creates. While this is merely a possible explanation not supported by any facts or findings in this paper, such hypotheses are interesting areas for future research.

Lastly, evaluating figure 2 leads to another interesting observation. While the difference is variation is visible throughout the entire return series, the same does not go for comparing returns. Most definitely, the portfolio with higher beta-deltas outperforms the bottom portfolio in the tail end of this series, indicating that a difference in returns is realized towards the last years in the sample. This could imply that differences between A-Days and N-Days are increasingly important, again serving as an argument for further research on the topic.

6. Conclusion

Past research has shown that uncertainty is priced in the cross-section of stock returns. This paper attempts a novel method of sorting stocks based on the differential between their announcement day and non-announcement day beta, and while it fails to find alpha by comparing stocks with high and low beta-deltas, several interesting findings are brought to light. Portfolios containing stocks with a high beta-delta are less sensitive to market movements, and incur different factor loadings when evaluated with a model accounting for the Fama & French (2015) five factors and momentum. Especially the size, profitability, and momentum display differences between the top and bottom portfolios. While the significance of the tests in this paper are perhaps not to the level the author had hoped, it provides ample room for future research in the field, and shows robust relations in terms of volatility and beta-delta.

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Appendix A – Univariate sorts

Table A-1

Univariate sorts (Top 10 A-Days, 252-Day rolling windows)

This table presents the results of creating decile portfolios when sorting for beta-delta. The top portfolio contains the stocks with the largest beta-delta at the beginning of each month. Portfolios are rebalanced monthly. Column 1 and 2 present the mean A-Beta and N-Beta in each portfolio respectively. Column 3 presents the annualized return of each portfolio, with the annualized standard deviation in parentheses. Column 4 presents the Sharpe ratio of each portfolio. Lastly, columns 5, 6, and 7 present the alphas (as an annual percentage) generated when the return series of each portfolio are regressed on model 4, 5, and 6 as described in the methodology section. T-Statistics can be found in parentheses. Panel A contains all value weighted returns, while panel B presents the equal weighted variants.. The sample period was 1999-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Top	0.25	0.27	0.1344	0.91	0.60 (3.832)***	0.51 (3.781)***	0.22 (1.699)
			(0.1475)				
9	0.21	0.22	0.1219	0.69	0.46 (2.273)*	0.32 (1.872)	0.20 (1.180)
			(0.1779)				
8	0.18	0.19	0.1106	0.52	0.28 (1.252)	0.15 (0.733)	0.11 (0.555)
			(0.2110)				
7	0.16	0.17	0.1508	0.77	0.66 (2.826)**	0.50 (2.541)*	0.43 (2.110)*
			(0.1953)				
6	0.15	0.15	0.0683	0.33	-0.00 (-0.008)	-0.14 (-0.647)	0.07 (0.319)
			(0.2102)				
5	0.14	0.14	0.065	0.27	-0.05 (-0.175)	-0.20 (-0.772)	-0.07 (-0.253)
			(0.2379)				
4	0.13	0.13	0.0951	0.39	0.22 (0.693)	0.08 (0.283)	0.21 (0.718)
			(0.2415)				
3	0.12	0.12	0.0528	0.20	-0.02 (-0.048)	-0.17 (-0.500)	0.17 (0.473)
			(0.2633)				
2	0.11	0.11	0.2058	0.67	1.02 (2.375)*	0.84 (2.159)*	1.17 (2.862)**
			(0.3054)				
Bottom	0.11	0.11	0.0975	0.36	0.27 (0.706)	0.06 (0.185)	0.19 (0.519)
			(0.2746)				
Panel B							
Top	0.25	0.27	0.1279	0.86	0.20 (2.434)*	0.17 (2.016)*	0.06 (0.832)
			(0.1481)				
9	0.21	0.22	0.1265	0.74	0.07 (1.009)	0.064 (0.924)	0.01 (0.165)
			(0.1698)				
8	0.18	0.19	0.1443	0.82	0.16 (2.649)**	016 (2.590)**	0.14 (2.203)*
			(0.1768)				
7	0.16	0.17	0.1302	0.70	0.01 (0.245)	0.00 (0.072)	0.05 (0.986)
			(0.7026)				
6	0.15	0.15	0.1269	0.64	-0.06 (-1.176)	-0.01 (-1.256)	-0.02 (-0.324)
			(0.1974)				
5	0.14	0.14	0.1232	0.62	-0.10 (-1.595)	-0.11 (-1.673)	-0.09 (-1.427)
			(0.2002)				
4	0.13	0.13	0.1334	0.63	-0.09 (-0.793)	-0.09 (-1.029)	0.02 (0.264)
			(0.2127)				
3	0.12	0.12	0.1303	0.62	-0.08 (-0.792)	-0.08 (-0.843)	-0.01 (-0.086)
			(0.2118)				
2	0.11	0.11	0.1337	0.62	-0.07 (-0.590)	-0.08 (-0.723)	0.03 (0.252)
			(0.2147)				
Bottom	0.11	0.11	0.1048	0.49	-0.27 (-2.534)*	-0.28 (-2.539)*	-0.14 (-1.302)
			(0.2126)				

Significance levels: *** (0.001), ** (0.01), * (0.05)

Table A-2

Univariate sorts (Top 10 A-Days, 60-Day rolling windows)

This table presents the results of creating decile portfolios when sorting for beta-delta. The top portfolio contains the stocks with the largest beta-delta at the beginning of each month. Portfolios are rebalanced monthly. Column 1 and 2 present the mean A-Beta and N-Beta in each portfolio respectively. Column 3 presents the annualized return of each portfolio, with the annualized standard deviation in parentheses. Column 4 presents the Sharpe ratio of each portfolio. Lastly, columns 5, 6, and 7 present the alphas (as an annual percentage) generated when the return series of each portfolio are regressed on model 4, 5, and 6 as described in the methodology section. T-Statistics can be found in parentheses. Panel A contains all value weighted returns, while panel B presents the equal weighted variants.. The sample period was 1999-2019

Panel A							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Top	0.24	0.24	0.0929 (0.1425)	0.65	0.29 (1.848)	0.22 (1.726)	0.01 (0.118)
9	0.19	0.20	0.1150 (0.1763)	0.65	0.38 (1.938)	0.30 (1.804)	0.24 (1.389)
8	0.17	0.17	0.1159 (0.2047)	0.56	0.30 (1.384)	0.22 (1.179)	0.13 (0.669)
7	0.15	0.16	0.0879 (0.2138)	0.41	0.06 (0.293)	-0.00 (-0.008)	0.03 (0.158)
6	0.14	0.14	0.1028 (0.2176)	0.47	0.17(0.753)	0.10 (0.472)	0.18 (0.897)
5	0.13	0.13	0.1413 (0.2496)	0.57	0.50 (1.59)	0.41 (1.482)	0.82 (3.007)**
4	0.12	0.12	0.0800 (0.2274)	0.35	0.06 (0.204)	-0.03 (-0.104)	0.17 (0.695)
3	0.11	0.11	0.1104 (0.3052)	0.36	0.32 (0.752)	0.24 (0.626)	0.54 (1.419)
2	0.10	0.10	0.0265 (0.2839)	0.09	-0.44 (-1.279)	-0.51 (-1.618)	-0.18 (-0.581)
Bottom	0.10	0.10	0.1714 (0.3509)	0.49	0.80 (1.539)	0.69 (1.438)	1.14 (2.403)*
Panel B							
Top	0.24	0.24	0.1207 (0.1299)	0.93	0.47 (3.925)***	0.43 (4.119)***	0.11 (1.159)
9	0.19	0.20	0.1220 (0.1643)	0.74	0.31 (3.064)**	0.28 (3.078)**	0.06 (0.746)
8	0.17	0.17	0.1106 (0.1838)	0.60	0.13 (1.753)	0.12 (1.633)	0.02 (0.231)
7	0.15	0.16	0.1020 (0.2024)	0.50	-0.01 (-0.101)	-0.01 (-0.149)	-0.03 (-0.578)
6	0.14	0.14	0.1090 (0.2159)	0.51	-0.00 (-0.009)	0.00 (0.053)	0.01 (0.262)
5	0.13	0.13	0.1026 (0.2317)	0.44	-0.09 (-1.444)	-0.09 (-1.321)	0.02 (0.235)
4	0.12	0.12	0.1020 (0.2440)	0.42	-0.13 (-1.773)	-0.12 (-1.655)	-0.02 (-0.285)
3	0.11	0.11	0.0969 (0.2493)	0.39	-0.18 (-2.164)*	-0.16 (-2.042)*	-0.03 (-0.322)
2	0.10	0.10	0.0900 (0.2558)	0.35	-0.25 (-2.536)*	-0.23 (-2.486)*	-0.10 (-1.098)
Bottom	0.10	0.10	0.0896 (0.2579)	0.35	-0.25 (-2.268)*	-0.22 (-2.132)*	-0.04 (-0.350)

Significance levels: *** (0.001), ** (0.01), * (0.05)

Table A-3

Univariate sorts (Top 4 A-Days, 252-Day rolling windows)

This table presents the results of creating decile portfolios when sorting for beta-delta. The top portfolio contains the stocks with the largest beta-delta at the beginning of each month. Portfolios are rebalanced monthly. Column 1 and 2 present the mean A-Beta and N-Beta in each portfolio respectively. Column 3 presents the annualized return of each portfolio, with the annualized standard deviation in parentheses. Column 4 presents the Sharpe ratio of each portfolio. Lastly, columns 5, 6, and 7 present the alphas (as an annual percentage) generated when the return series of each portfolio are regressed on model 4, 5, and 6 as described in the methodology section. T-Statistics can be found in parentheses. Panel A contains all value weighted returns, while panel B presents the equal weighted variants.. The sample period was 1999-2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A							
Top	0.30	0.33	0.1209 (0.1315)	0.92	0.24 (2.150)*	0.26 (2.483)*	0.16 (1.572)
9	0.24	0.26	0.1283 (0.1723)	0.74	0.12 (0.762)	0.19 (1.333)	0.19 (1.340)
8	0.21	0.23	0.1225 (0.1889)	0.65	0.03 (0.178)	0.11 (0.635)	0.05 (0.289)
7	0.19	0.20	0.0883 (0.2168)	0.41	-0.27 (-1.043)	-0.20 (-0.822)	-0.04 (-0.158)
6	0.17	0.18	0.1000 (0.2028)	0.49	-0.14 (-0.629)	-0.05 (-0.252)	-0.04 (-0.225)
5	0.16	0.16	0.0817 (0.2212)	0.37	-0.37 (-1.557)	-0.30 (-1.377)	-0.23 (-1.097)
4	0.15	0.15	0.1508 (0.2349)	0.64	0.30 (0.880)	0.39 (1.190)	0.46 (1.401)
3	0.13	0.13	0.0466 (0.2134)	0.22	-0.48 (-1.642)	-0.38 (-1.423)	-0.33 (-1.183)
2	0.12	0.12	0.1574 (0.2388)	0.66	0.34 (0.983)	0.42 (1.276)	0.45 (1.313)
Bottom	0.12	0.12	0.0716 (0.2609)	0.27	-0.39 (-1.049)	-0.30 (-0.838)	-0.14 (-0.416)
Panel B							
Top	0.30	0.33	0.1157 (0.1383)	0.84	0.18 (1.828)	0.14 (1.447)	0.01 (0.094)
9	0.24	0.26	0.1142 (0.1626)	0.70	0.02 (0.300)	0.02 (0.228)	-0.08 (-0.969)
8	0.21	0.23	0.1225 (0.1784)	0.69	-0.00 (-0.010)	0.01 (0.173)	-0.06 (-0.890)
7	0.19	0.20	0.1180 (0.1832)	0.64	-0.06 (-0.990)	-0.06 (-0.8)	-0.08 (-1.424)
6	0.17	0.18	0.1283 (0.1912)	0.67	-0.03 (-0.515)	0.01 (0.100)	0.03 (0.476)
5	0.16	0.16	0.1342 (0.1961)	0.68	-0.01 (-0.098)	-0.01 (-0.210)	-0.04 (-0.590)
4	0.15	0.15	0.1311 (0.2065)	0.63	-0.07 (-0.933)	-0.06 (-0.831)	-0.01 (-0.170)
3	0.13	0.13	0.1352 (0.2011)	0.67	-0.01 (-0.177)	-0.01 (-0.105)	0.08 (1.104)
2	0.12	0.12	0.1435 (0.2059)	0.70	0.03 (0.378)	0.04 (0.389)	0.11 (1.212)
Bottom	0.12	0.12	0.1364 (0.2186)	0.62	-0.06 (-0.497)	-0.07 (-0.600)	0.04 (0.67)

Significance levels: *** (0.001), ** (0.01), * (0.05)

Appendix B – Bivariate sorts

Table B-2

Bivariate sorts (Top 10 A-Days, 60 day rolling window)

Each panel presents both a priori A-Beta sorted and N-beta sorted portfolios, which are subsequently sorted by beta-delta. Panel A contains all value weighted portfolios, whereas the equal weighted ones are presented in panel B. Section (a) for both panels presents the A-Beta sorted portfolios, with the N-Beta sorted portfolios in section (b). For each section, column 1 presents the annualized return on each quintile portfolio, with the annual standard deviation in parentheses. Column 2 then presents the associated Sharpe ratio, with the alphas generated by regressing the return series on model 6 presented in column 3. The T-statistics are reported in the parentheses. The sample period was 1999-2019.

Panel A

	(a) A-Beta sorted			(b) N-Beta sorted		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Top	0.1080	0.7115	0.23 (1.823)	0.1124	0.7030	0.23 (1.712)
	(0.1518)			(0.1599)		
4	0.1179	0.6204	0.20 (1.175)	0.0895	0.4708	0.10 (0.630)
	(0.1901)			(0.1901)		
3	0.1089	0.4668	0.44 (1.764)	0.1507	0.6304	0.76 (2.914)**
	(0.2332)			(0.2390)		
2	0.1122	0.5071	0.23 (1.231)	0.1026	0.4538	0.20 (0.919)
	(0.2214)			(0.2262)		
Bottom	0.1201	0.5222	0.42 (2.366)*	0.1141	0.4512	0.44 (1.884)
	(0.2300)			(0.252)		
			Panel B			
Top	0.1182	0.7811	0.09 (1.457)	0.1211	0.7880	0.08 (1.167)
	(0.1513)			(0.1537)		
4	0.1064	0.5300	-0.03 (-0.667)	0.1119	0.5550	-0.01 (-0.124)
	(0.2008)			(0.2016)		
3	0.0992	0.4407	-0.10 (-2.270)*	0.1010	0.4525	-0.08 (-1.921)
	(0.2251)			(0.2232)		
2	0.1044	0.4499	-0.03 (-0.592)	0.0982	0.4220	-0.08 (-1.599)
	(0.2320)			(0.2326)		
Bottom	0.0991	0.4138	-0.07 (-1.185)	0.095	0.3964	-0.05 (-0.803)
	(0.2395)			(0.2398)		

Significance levels: *** (0.001), ** (0.01), * (0.05)

Table B-2

Bivariate sorts (Top 4 A-Days, 252 day rolling window)

Each panel presents both a priori A-Beta sorted and N-beta sorted portfolios, which are subsequently sorted by beta-delta. Panel A contains all value weighted portfolios, whereas the equal weighted ones are presented in panel B. Section (a) for both panels presents the A-Beta sorted portfolios, with the N-Beta sorted portfolios in section (b). For each section, column 1 presents the annualized return on each quintile portfolio, with the annual standard deviation in parentheses. Column 2 then presents the associated Sharpe ratio, with the alphas generated by regressing the return series on model 6 presented in column 3. The T-statistics are reported in the parentheses. The sample period was 1999-2019.

	(a) A-Beta sorted			(b) N-Beta sorted		
Panel A						
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Top	0.1053	0.6928	0.07 (0.506)	0.0952	0.5896	-0.06 (-0.446)
	(0.1519)			(0.1614)		
4	0.1219	0.6851	0.11 (0.745)	0.1550	0.8858	0.43 (2.735)**
	(0.1779)			(0.1750)		
3	0.1170	0.5805	0.15 (0.726)	0.1138	0.6361	0.09 (0.565)
	(0.2016)			(0.1789)		
2	0.1329	0.6300	0.16 (0.913)	0.1420	0.6674	0.26 (1.203)
	(0.2109)			(0.2127)		
Bottom	0.1026	0.4373	-0.12 (-0.413)	0.0897	0.4342	-0.24 (-1.434)
	(0.2345)			(0.2066)		
Panel B						
Top	0.1166	0.7649	0.00 (0.049)	0.1222	0.7524	0.02 (0.294)
	(0.1525)			(0.1624)		
4	0.1192	0.6682	-0.08 (-1.397)	0.1298	0.7165	0.01 (0.121)
	(0.1794)			(0.1811)		
3	0.1397	0.7684	0.07 (1.593)	0.1355	0.7218	0.02 (0.395)
	(0.1891)			(0.1877)		
2	0.1371	0.6845	0.03 (0.567)	0.1309	0.6746	0.01 (0.204)
	(0.2002)			(0.1941)		
Bottom	0.1394	0.6694	0.06 (0.891)	0.1345	0.6726	0.02 (0.430)
	(0.2083)			(0.2000)		

Significance levels: *** (0.001), ** (0.01), * (0.05)

Appendix C – Macroeconomic announcements

Table C-1

The top 10 announcements as presented in the main body of this thesis

Announcement	Frequency	Category	First observation	Relevance
Panel A: Top 4 announcements				
GDP Annualized QoQ	Monthly	Output	1997	97
Change in Nonfarm payrolls	Monthly	Employment	1997	99
Conf. Board consumer confidence	Monthly	Sentiment	1997	94
CPI MoM	Monthly	Inflation	1998	96
Panel B: Remaining 6				
ISM Manufacturing	Monthly	Output	1996	95
Initial jobless claims	Weekly	Employment	1997	98
New home sales	Monthly	Output	1997	91
Durable goods orders	Monthly	Output	1997	93
U. of Mich. Sentiment	Twice a month	Sentiment	1999	94
Retail Sales Advance MoM	Monthly	Output	2001	92

Table C-2
All remaining announcements that are part of the surprise index

Announcement	Frequency	First observation	Relevance
Personal Income	Monthly	1998	85
Factory Orders	Monthly	1998	86
Consumer credit	Monthly	1998	39
Industrial Production MoM	Monthly	1998	90
Philadelphia Fed Business Outlook	Monthly	1998	80
Monthly budget statement	Monthly	1998	76
MNI Chicago PMI	Monthly	1998	82
Trade Balance	Monthly	1998	84
Unemployment rate	Monthly	1998	89
CPI Ex Food and Energy MoM	Monthly	1998	77
Capacity Utilization	Monthly	1998	63
Employment Cost Index	Quarterly	1998	75
Personal Spending	Monthly	1998	85

Business Inventories	Monthly	1998	39
Nonfarm productivity	Quarterly	1999	43
New Home Sales	Monthly	1998	91
Durable Goods Orders	Monthly	1998	93
Current Account Balance	Quarterly	1998	73
Housing Starts	Monthly	1998	89
Import Price Index	Monthly	1998	78
Change in Manufact. Payrolls	Monthly	1999	69
ISM Prices Paid	Monthly	2000	74
Retail Sales ex Auto MoM	Monthly	1998	64
Durables Ex Transportation	Monthly	2001	74
Continuing Claims	Weekly	2002	69
Building Permits	Monthly	2002	62
Empire Manufacturing	Monthly	2002	83
CPI Ex Food and Energy YoY	Monthly	1998	77
Personal Consumption	Quarterly	2003	68
NAHB Housing Market Index	Monthly	2003	46
Construction Spending MoM	Monthly	1998	80
PCE Core Deflator YoY	Monthly	2004	50
Pending Home Sales MoM	Monthly	2005	76
GDP Price Index	Quarterly	1999	77
PCE Core Deflator MoM	Monthly	2004	50
Richmond Fed Manufact. Index	Monthly	2005	71
ADP Employment Change	Monthly	2006	87
ISM Non-Manufacturing Index	Monthly	1999	79
FHFA House Price Index MoM	Monthly	2008	69
Pending Homes Sales NSA YoY	Monthly	2005	76
NFIB Small Business Optimism	Monthly	2010	62
Housing Starts MoM	Monthly	1998	89
Average Hourly Earnings MoM	Monthly	1998	31
Average Hourly Earnings YoY	Monthly	2010	32
Average Weekly Hours All Empl.	Monthly	1999	26
Cap Goods Orders Nondef Ex Air	Monthly	2010	60
PPI Final Demand MoM	Monthly	1998	87
PPI Ex Food and Energy MoM	Monthly	1998	66