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Anomalies and Spill Over Effects Induced by US Unemployment Press Releases:

An Event Study of the Stock Market

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Abstract

The primary purpose of this thesis is to analyze how the US unemployment rate affects the US market and markets overseas, the latter called spill over effects. Assuming that the anticipated outcome of the monthly unemployment announcement already is incorporated in stock prices, we aim at only studying the *unanticipated* news. This kind of news contains a surprise element that, if a connection between unemployment and stock market exists, should cause an adjustment in the equity prices. A secondary point of the study is to investigate if there are indications of market inefficiency in markets overseas.

Our expectations are that unanticipated unemployment rate *should* affect stock markets, especially small, dependant markets like the Swedish, through a series of macroeconomic variables. Also we expect that *positive news*, meaning lower than expected unemployment rate, should cause a rise in equity prices, and vice versa. If we find indications of inefficiency we deem it more likely to occur on small, illiquid markets than on larger, liquid markets.

Using market forecasts and real unemployment rate for 49 consecutive months to calculate unanticipated unemployment rate, we find that positive news are indeed valued higher than negative news, although, due to a small sample, the effect is not statistically significant.

Using different regression models to estimate forecasts of unemployment rate for 130 consecutive months, yields results that are contradictory to our expectations—good news seems to lower equity prices and vice versa. We also find that in all markets, stock return is higher than normal on the day of the press release, *regardless* of the information content.

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1 Introduction

In media, macroeconomic variables are often held accountable for movements in the stock market. The effect of the macroeconomic information is often related to some kind of stock index. This is logical since, if macroeconomic news has any impact, it will affect not just one firm, but rather the whole economy. For instance, in an article in SDS from May 9th, 2005, the unemployment rate in USA for April is reported to be lower than expected. The article states, "…the latest unemployment information caused a sigh of relief on the financial markets", and goes on about this being good news for the American business cycle. Furthermore it argues that the Federal Reserve has to strike a balance when deciding the interest rate; on one hand the higher expected inflation caused by the lower unemployment calls for an increased interest rate and on the other hand the interest rate need to be low enough to maintain economic growth. This is one example of the common belief that macroeconomic variables such as unemployment, inflation, interest rates are finely intertwined and have effects on economic growth which in turn affects equity prices. Using the techniques of an event study we examine if we can find evidence that supports the belief that one particular macroeconomic variable, namely news of unemployment in the US, affects prices of equity.

Also if the economy from which a macroeconomic event originates is powerful enough, it is plausible that this could generate spill over effects in economies in *other* parts of the world. Using the US market as our powerful economy we analyze the spill over effects on several markets worldwide, caused by news of US unemployment, in addition to analyzing the effect on the internal US market.

Some research from economists, e.g., McQueen and Roley (1993) uses business cycles to categorize the dates of macroeconomic events into groups, because they believe that market response to macroeconomic news differs across cycles. The information used to categorize events is partly based on posterior data. McQueen and Roley (1993) uses the natural log of Industrial Production over a period of eleven years and regress this. The regression results in a trend and they create an interval around this trend by adding and subtracting an arbitrary offset.

Periods which are above this interval are categorized as expansive, periods below are regarded as contractive, and periods inside the interval are regarded as a control group. As noted above, in order to calculate the trend, Industrial Production data over the whole period is used. This means that information not available at the time of the event is used to create a model used to analyze the effects of macroeconomic events.

Another example of an anti-causal study is one conducted by Boyd *et al.* (2005). They use the classification made by National Bureau of Economic Research (NBER) to categorize events into two groups; events during contractions and events during expansions. NBER also uses information *after* the event to classify periods. Market participants at the time of the event naturally don't have access to this kind of information. If we can establish that news of unemployment *do* affect stock prices, we proceed by investigating if excess returns can be generated by market participants around the time of the event using only information available prior to the event. If excess returns, based on historical information, can be generated this implies that the market is inefficient in pricing securities. Two reasons this could happen are:

1. prices don't fully reflect information available on the market, i.e., the anticipated outcome of the event is not fully incorporated in the price,
2. market reacts slowly to the event

If the semi-strong form of the Efficient Market Hypothesis see Subsection 2.1.1, exists then only unanticipated information about unemployment should have any impact on the stock market and this impact should quickly be incorporated in the stock prices. Therefore, if we can find excess returns, we have indication against this form of the Efficient Market Hypothesis.

1.1 Purpose

Our purpose with this thesis is threefold. The first point of interest is whether or not news of unemployment in the US has any effect on stock indices in the US. If the unemployment announcements affect the stock prices internally, we proceed by analyzing the spill over effects on other economic regions. Which types of economies are affected? Is the effect different on small and larger markets? For example, is the effect significantly different on a small market like the Swedish, compared to a more liquid market such as the UK market? We also include the German, French and Japanese market in our study.

Finally, do the different markets effectively absorb the information and thus make it impossible for investors to generate excess returns based on the models presented in this thesis?

1.2 Our approach

In the introduction above we described how contemporary researchers categorized periods as expansive and contractive based on future information relative to that point in time. In contrast to these anti causal studies, our aim is to keep this study causal. Therefore we will use another way of categorizing events. We will categorize the events based on the unanticipated information in each event, i.e., if the announced unemployment rate is below the expected, the event will be categorized as *positive*, and vice versa. If we don't divide the events into positive and negative groups we suspect that any result we might find would be biased to zero, i.e., the effect from the positive and negative group would cancel each other out. If our statistical analysis shows significant abnormal return, i.e., return above the normal return, for either group, market participants could take action on the days around the event to reap the reward.

1.2.1 Data and periods

Our primary data consists of monthly unemployment rates and the corresponding release dates from June 1987 to April 2005. To create our estimate for unemployment rates we also use monthly industrial production growth rates, change in monthly 3-month Treasury Bill rates, and monthly default yield spread between Baa and Aaa[1] corporate bonds. All the above data is gathered at Russian Full Service Investment Company

In our study of effects on the US market and spill over effects on the German, UK, Japanese, French, and Swedish markets we employ daily returns from corresponding indices to calculate mean normal returns and abnormal returns,

[1] Aaa bonds are bonds of the highest quality that offer the lowest degree of investment risk. Issuers are considered to be extremely stable and dependable. Baa bonds are bonds of medium grade quality. Security currently appears sufficient, but may be unreliable over the long term.

starting in July 1993 and ending in April 2005. The indices we use are provided by Morgan Stanley.

1.3 Expectations

Negative information regarding unemployment, meaning anticipated unemployment is smaller than announced unemployment for a certain period, could result in two possible outcomes. Our immediate expectation is that higher than expected unemployment would lead to lower total profit and thus lower aggregate growth rates across the economy which in turn would lead to lower stock prices. However companies that have given people the pink slip in order to render their organization more effective and thus generate more profits, could exhibit equal or even higher growth rates. We expect that the first outcome is more probable than the second. Thus we anticipate that the market will react negatively by selling securities which will result in lower stock index returns, as a response to negative news. By the same reasoning we expect that positive news would lead to higher stock index returns.

1.4 Outline

In Chapter 2 we will describe the theories for market efficiency and valuation of individual securities. In Chapter 3, we describe the different unemployment forecast models we make use of to categorize events, how the event study is performed and what model selections we have made for this event study, and finally what data we use for this study. Our results are presented in Chapter 1 with plots of abnormal returns for each country. For statistical figures and cumulative abnormal returns, see Appendix C. In Chapter 5 we sum up this thesis and present our conclusion and discourse on possible sources of error.

2 Theoretical Framework

A market is defined as a place in which firms can make capital investment decisions and where speculators can invest in securities—an ownership representation. Traded resources are allocated according to their prices, i.e., prices contains information for an efficient resource allocation. This allocation of resources is efficient under the assumption that prices fully reflect all available information at any time, which is the same as saying that the market is efficient.

Below we present the often quoted work regarding the Efficient Market Hypothesis by Fama (1970).

2.1 Efficient Market Hypothesis

Investopedia defines The Efficient Market Hypothesis as "The EMH is a highly controversial and often disputed theory. Supporters believe it is pointless to search for undervalued stocks or try to predict trends in the market through any technique from fundamental to technical analysis, since an individual could achieve superior results from randomly picking stocks from a hat."

When the current price of an asset fully reflects all available information then the market is regarded as efficient. According to Fama (1970) there are three sufficient conditions for capital market efficiency:

i. there are no transaction costs in trading securities,
ii. all available information is costlessly available to all market participants, and
iii. all agree on the implications of current information for the current price and distributions of future prices of each security.

These conditions summarize a frictionless market and are sufficient for market efficiency, but not necessary.

There are three different forms of efficiency and each of those is briefly described below.

2.1.1 Weak

The weak form of EMH states that the price of an asset reflects all historical price information. This implies that, solely based on previous movements on the stock market, an investor will be unable to receive excess returns. In order to test for this form of efficiency historical data is used to locate cyclical behaviours in stock prices to predict future stock price movements. If excess returns are generated using these predictions, then the weak form of efficiency won't hold.

2.1.2 Semi-strong

The semi-strong form of EMH states that all historical and publicly available information is fully reflected in the stock prices. Also the market should immediately react to new information and adjust stock prices accordingly. One way of testing for this form of efficiency is by employing event studies.

The immediate reaction to new information is fundamental for a semi-strong market. If all investors can't grasp the revealed information, then the market will react slowly to the new information, hence the uninformed investors will react irrational and the stock price won't fully reflect all available information.

2.1.3 Strong

According to Fama (1970) the strong form of EMH implies that "…no individual has higher expected trading profits than others because he has monopolistic access to information". This form of efficiency is, strictly interpreted, rather naive, since there always exists insiders, like CEO:s and market makers, who have monopolistic access to information. Testing for this kind of efficiency therefore boils down to measuring the value of hunting information. This can be done by comparing the performance of different mutual funds or investment firms. If systematic differences exists this would be evidence against the strong form of EMH. An example of a value investor who has outperformed the market by a large margin is Warren Buffet who, in the course of the last 40 years has outperformed S&P500 by a factor 60!

2.2 Random Walk Hypothesis

The Brownian motion, i.e., a Random walk process, originates from the 19th century English botanist, Robert Brown. He studied particle movements in fluid and noticed peculiar inconsistent movements of the particles, Kač (1947). From the original work by Brown a more advanced and complete theory has evolved, contributors to this theory are among others a famous collection physicists; Feynman and Kač with their heat equation, Fokker and Planck with a statistical description of BM, and Einstein who considered the case of free particles[2].

There are two prevailing methods to predict stock market prices. The first method is chartist[3] or technical analysis, this method is based upon the assumption that past patterns of price behaviour in individual securities will tend to recur in the future. The techniques of chartist have always been surrounded with certain mysticism, e.g., applying Fibonacci series to security price movements. The other method is the fundamental or intrinsic value analysis; an approach based on the assumption that at any point in time an individual security has an intrinsic value, which depends on fundamental factors such as quality of management and outlook of industry and economy. The actual security price strive towards the intrinsic value—an equilibrium price. With a correct performed fundamental analysis, the analyst can determine whether the actual security price is above or below the intrinsic value; and thus have predicted the future price, Fama (1965). Traditionally another approach has been used by the academic world, primarily economists and statisticians; and this is where the random walk gets in the picture.

In the major market places, often regarded as efficient markets, there are numerous of rational and intelligent participants competing, trying to predict future market values of individual securities. This lead to a situation where, at any point in time, asset prices already reflects the effects of information based on previous events and known future events. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value. However, since the exact intrinsic value is unknown in a uncertain world, there is always room for disagreements vis-à-vis the intrinsic value for an

[2] Imagine a particle which moves along the x-axis in such a way that in each step it can either go to the left or to the right. A free particle is interpreted by assuming the same probabilities for moving to the left as moving to the right; these equal probabilities imply a free particle.
[3] A stock-market specialist who uses charts and graphs to interpret market action, predict trends, or forecast price movements of individual stocks, Houghton Mifflin (2000).

individual security among market participants, and such disagreement will make leeway for discrepancies between actual price and the equilibrium price. In an efficient market, however, the actions of many competing participants should cause the actual price of a security to wander randomly about its intrinsic value. N.B. the intrinsic value may vary across time as a result of new information, Fama (1965).

New information will cause actual prices to fully reflect intrinsic values instantaneously on an efficient market. There is vagueness and uncertainty in new information, which gives rise to an ambiguity, instantaneous adjustment has two implications. First, actual prices will initially over adjust to changes in intrinsic values as often as they will under adjust. Second, the lag in the complete adjustment of actual prices to consecutive new intrinsic values will be an independent, random variable with the adjustment to the actual price sometimes preceding the occurrence of the event and sometimes following. When the event is anticipated by the market before it actually occurs, the adjustment to the actual value will precede the event, Fama (1965).

The properties mentioned in the previous section of an efficient market, e.g., instantaneous adjustment in individual security prices to new information, implies that successive price changes are independent. A market where consecutive price changes are independent is, by definition, a random walk market. The most powerful implication of the random walk theory is that, series of stock price changes has no memory—the past history of the series cannot be used to predict the future in any meaningful way.

Rasmus (2005) defines the BM as the following, let $W = \{W_t : t \in R_+\}$ be a stochastic process with the following four properties:

i. $W_0=0$

ii. *The increments are independent and stationary. That is, for* $0 \leq h \leq s \leq t$ (W_s-W_{s-h}) *is independent of* $(W_{t+h}-W_t)$ *and the distribution of* $(W_{t+h}-Wt)$ *depends only on the increments of the distance h.*

iii. *The distribution of an increment is* $(W_{t+h} - W_t) \in N(0, h)$

iv. W_t *has continuous paths.*

These definitions are important when describing stock movements, the second point give the internal structure and the third point gives the distribution of the process. Since the increments are independent there is no memory in the BM, Rasmus (2005).

If the stock market prices follow a random walk, then it should not be possible to generate excess returns based on historical movements in stock market prices. If we find significant abnormal returns in this study, then we have indications of non-efficient markets and thus indications against the EMH.

2.3 Fair Game

To make EMH testable, that is, somehow be able to test if securities (or in our case stock indices) "fully reflect" all the publicly available information, and thus having an efficient market, Fama (1970) uses a *fair game* model. He defines it as follows: If

$$z_{i,t+1} = r_{i,t+1} - E\left[\tilde{r}_{i,t+1} \middle| \Omega_t\right], \tag{2.1}$$

then,

$$E\left[\tilde{z}_{i,t+1} \middle| \Omega_t\right] = 0, \tag{2.2}$$

where $r_{i,t+1}$ is the actual return at time $t+1$, $E\left[\tilde{r}_{i,t+1} \middle| \Omega_t\right]$ is the expected value of the return at time $t+1$ projected at time t given the information at time t. In other words, if (2.2) holds, market investors shouldn't be able to generate excess returns if the market is efficient. In an event study, which is described in Subsection 3.3.1, abnormal returns are calculated. If these abnormal returns, corresponding to $z_{i,t+1}$ in (2.1), are significantly different from zero, this implies a non-efficient market.

2.4 A recent study

In a recent study conducted by Boyd *et al.* (2005) it is argued that responses to unemployment news are different during expansive periods of the economy than for contractive periods. They classify every sample month as a contractive month or an expansive month based on NBER:s classifications. The vast majority of the sample months are expansive, 297 vs. 46.Their unemployment rate data material stretches from June 1972 to December 2000. Boyd *et al.* make use of their own unemployment forecast model, because of lack of real market forecast data, in order "…to identify the surprise element of the unemployment rate announcement". They study the reaction on the S&P500 to unemployment rate announcements during the above period.

When analyzing their results they divide the effect on S&P500 from unemployment rate announcements into *three* different variables, namely changes in interest rate, growth expectations and risk premium demanded by market. They arrive at these variables by making use of Gordon's model,

$$P_t = \sum_{i=1}^{\infty} \frac{D_t (1+g)^i}{(1+k)^i},$$

where P_t is the price of the equity, D_t is the dividend paid at time t, g is the expected growth rate, and k is discount rate demanded by the market. Boyd *et al.* further divides k into r and π yielding:

$$P_t = \sum_{i=1}^{\infty} \frac{D_t (1+g)^i}{(1+r+\pi)^i},$$

where r is the risk free interest rate and π is the risk premium demanded by the market. This is an infinite geometric sum which is derived in Appendix A.

Based on their data they observe that interest rates fall in response to negative unemployment news during expansive periods, which causes stock prices to rise. This rise is somewhat hampered by negative future growth rate expectations and/or increased risk premium demanded by the market. During contractive periods interest rates are unaffected by unemployment news, but stock prices fall. This fall is then due to the same hampering factors as above.

This implies that we should also divide our sample into different states of the economy, but in order to keep our model causal, we cannot divide the sample the same way as Boyd *et al.* (2005), who used NBER:s classifications of economic state, which is made after the event took place: Remember, that we try to create a model useable by investors around the time of a press release and thus can't make use of NBER's classification, since we then would use information not available at the time of the event. If by using our model, we can't generate excess returns, we don't have any indications that the market is inefficient.

2.5 Phillips-curve

Alban William Phillips is the name of a national economist from New Zealand who claimed that there existed a negative relationship between unemployment and inflation in Great Britain, during the years 1861-1957. The American national economists Paul Samuelsson and Robert Solow found a similar pattern in the US and coined the concept “Phillips-curve”, Fregert (2003). Research throughout the last 40-50 years, though, has found little such evidence in the long run, but more so in the *short run*. For instance, an expansive financial policy will yield more jobs in the near future, but experience shows that wages and prices and therefore inflation rise as a result of this while the unemployment eventually revert to the initial level.

As long unemployment and inflation are negatively correlated, although only in the short run, we expect the unemployment rate changes to affect inflation which in turn would affect interest rates and equity prices. This is in accordance with the results of the study by Boyd *et al.* (2005). Boyd found that interest rate is positively correlated with the news, i.e., negative news causes a fall in the interest rate and positive news cause a rise in the interest rate. If the level of the interest rate is positively correlated with the level of inflation, by no means a farfetched assumption, then the results of Boyd speaks in favour of the Phillips curve in the short run.

3 Data and Methodology

In this chapter we will present the procedure by which we conduct this analysis. We are going to follow the methods of an event study, using three different models to categorize each unemployment press release (called event), calculate abnormal returns, and finally test for statistical significance. First, however, we will present the data that is used in this study.

3.1 Data

Our primary data consists of monthly unemployment rates and the corresponding release dates from June 1987 to April 2005. Due to reasons discussed in Subsection 3.2, sometimes only part of the sample is used in the estimation of abnormal returns. Each press release contains the initial assessment of the previous month's unemployment. These unemployment figures are subsequently revised by the Department of Labor Statistics, but we use the initial values in order to make our study causal. To create our estimate for unemployment rates we also use the following monthly data: industrial production growth rates from April 1987 to March 2005, change in 3-month Treasury Bill rates from June 1987 to March 2005, and default yield spread between Baa and Aaa corporate bonds for the same period as for Treasury Bills. Since the news of industrial production growth rates is released one to two weeks after the unemployment news, we can't use the figures from the same month when forecasting future unemployment; see Subsection 3.2. All the above data was gathered at Russian Full Service Investment Company.

In our study of the effect on the US market and possible spill over effects on the German, UK, Japanese, French, and Swedish markets we use daily returns from corresponding indices to calculate mean normal returns and abnormal returns. The indices we use are provided by Morgan Stanley and the period ranges from July 1993 to April 2005. All of the indices are given in local currency, so that changes in foreign exchange rates won't pollute our results. We have included the index for USA as a reference, because if the unanticipated unemployment rate doesn't affect the reference index it is unlikely it should have any effect on markets overseas. Our index data contains some missing values and some values where the return is zero, i.e., the index values are constant over several days. Both the missing values and the zero returns are removed from the original data; we consider both to be the effect of non-trading days on the different stock exchanges. Therefore the event day on a stock index does not always coincide with the date for unemployment press releases. Where this happens we move the event day on the stock index to the earliest following trading day after the unemployment press release.

In order to manage all data efficiently and be able to use automated generic routines we have imported all data together with the corresponding dates. The root to our first problem was the use of different date formats, e.g., mm/dd/yy will be sorted according to the month, dd-mm-yy will be sorted according to the day. To solve this we created a MATLAB function (see Appendix B) to convert all dates to a universal date format. It would have been nice to use a date format based on the yyyy-mm-dd format; this format only has one inherited drawback, it is saved as an array of ASCII characters in MATLAB. As an alternative we use a date format with close kinship to the yyyy-mm-dd format, using numerals counting from year zero increasing by one per day; the pros are a comparable date format, the cons are less readability. Having done this conversion, all data, e.g., stock indices, bond rates, etc can easily be mapped to the corresponding event. Our adaptive estimation window, see below, are easily extracted from the stock index merely by comparing date numerals.

3.2 Unemployment forecast

In order to analyze the effect of unemployment on the various stock indices, we define the unanticipated unemployment rate, UUR_t, as:

$$UUR_t = FUR_t - RUR_t, \tag{3.1}$$

where t is the time for a press release, RUR_t is the officially announced unemployment rate at time t, and FUR_t is the forecasted unemployment rate for the same time. According to EMH the anticipated unemployment rate is already fully reflected in the price, in this case our stock indices. Therefore it's really the unanticipated unemployment that should affect the returns of the stock indices, e.g., if UUR_t is zero then we would not expect any changes in returns, since no new information is revealed. If UUR_t on the other hand is positive we call this positive news and if UUR_t is negative we call it negative news. We conduct unemployment forecasts in three different ways.

1. Using the services of the Russian Full Service Investment Company we have been able to gather market expectations for the US unemployment rate for 49 consecutive months, from April 2001 to April 2005. This data, together with the real unemployment rates is used to calculate UUR_t.

2. Since the sample above is relatively small we deemed it necessary to compare the results using that classification with a model using a larger sample. Therefore we also employ a forecast model inspired by Boyd *et al.* (2005):

$$\begin{aligned} \Delta RUR_t = b_0 + b_1 \cdot IPGR_{t-1} + b_2 \cdot IPGR_{t-2} + b_3 \cdot IPGR_{t-3} \\ + b_4 \cdot \Delta RUR_{t-1} + b_5 \cdot \Delta TB3_{t-1} + b_6 \cdot \Delta BA_{t-1} + \varepsilon_t, \end{aligned} \tag{3.2}$$

where ΔRUR_t is the change in real unemployment rate from time $t\text{-}1$ to t, $IPGR_{t-1}$ to $IPGR_{t-3}$ are three lagged terms of the industrial production growth rate, $\Delta TB3_{t-1}$ is the previous month's change in 3-month T-Bill rate, ΔBA_{t-1} is the previous month's change in default yield spread between Baa and Aaa corporate bonds, and ε_t is a normally distributed error term. We use a window of 84 observations, which is 7 years of data, to calculate b_1 through b_6. The reason for this window size is that it yields the smallest Mean Squared Forecast Error (MSFE), see below. The estimated parameters b1 through b6 are used to forecast unemployment rate change for the next month as follows:

$$\begin{aligned} FUR_t &= E[\Delta RUR_t | \Omega_{t-1}] + RUR_{t-1} \Rightarrow \\ UURt &= E[\Delta RUR_t | \Omega_{t-1}] + RUR_{t-1} - RURt \\ &= E[\Delta RUR_t | \Omega_{t-1}] - \Delta RURt, \end{aligned} \tag{3.3}$$

where Ω_{t-1} is the available information up to and including time $t\text{-}1$. After FUR_t is calculated, the window is moved one step in order to calculate FUR_{t+1}, and so on. This yields a sample of 130 events, from July 1994 to April 2005, grouped as either positive or negative news.

3. Finally we would like to compare our result using our forecast model above, with another simple forecast method using only the previous unemployment rate as a forecast of the next,

$$\begin{aligned} FUR_t &= RUR_{t-1} \Rightarrow \\ UUR_t &= RUR_{t-1} - RUR_t = -\Delta RUR_t . \end{aligned} \tag{3.4}$$

As above we get a sample of 130 events.

As a measure of how well the different models are able to forecast the real unemployment rate we calculate the Mean Squared Forecast Error (MSFE),

$$MSFE = \frac{1}{n}\sum_{t=1}^{n}\left(FUR_t - RUR_t\right)^2 \tag{3.5}$$

The MSFE for each of the above models is discussed in Chapter 5.

3.3 Event study

An event study is used to determine the effect of economic events on the value of a security. In our case the "security" is the various stock indices, i.e., the regional economies associated with each index. According to Asgharian the following steps are involved:

Event definition: We define the event as the press release from the U.S. Department of Labor, Bureau of Labor Statistics regarding the US unemployment rate. These press releases occur in the beginning of each month on a Friday 8.30 A.M. In order to see impact of the information the days around the press release are studied. This is called the *event window*. We use a symmetric event window starting at *t-2* and ending at *t+2*, where t is the time of the event. The reason we include two days before the time of the event, is that we want to capture any form of speculative activity prior to the event. If the market reacts to the information we expect to see significant abnormal return (see below) at the time of the event and possibly the days after the event, for the positive and negative group respectively. Since the unemployment press releases are made on regular basis we expect the market to make immediate adjustments to new information. Therefore we keep a small post event window of 2 days, which should be enough to discover if the market works inefficiently.

Selection criteria: In our study we include six stock indices; Morgan Stanley's indices for USA, UK, Germany, France, Sweden and Japan. We examine how these react to the press releases mentioned above.

Measuring normal and abnormal returns: We define return as the daily relative change in index value,

$$R_{i,t} = \frac{IV_{i,t} - IV_{i,t-1}}{IV_{i,t-1}},$$

where $IV_{i,t}$ is the index value for stock index i at time t. The return, conditional on Ω_t,

$$E\left[R_{i,t} \middle| \Omega_t\right], \tag{3.6}$$

where Ω_t is the information up to time t, is the normal return that would be expected if the event did not take place. There are different methods of calculating normal return, two of them being the market model and the constant mean model. The market model assumes non constant information and uses the market return as a proxy for the information Ω_t. The market model assumes a linear relationship between the individual return and the market return and is estimated using an Ordinary Least Squares (OLS) regression, developed by Fama, Fisher, Jensen, and Roll (1969):

$$R_{i,t} = \alpha + \beta R_{m,t} + \varepsilon_{i,t}, \tag{3.7}$$

where $R_{m,t}$ is the market return. The calculated parameters α and β, which are assumed to be constant throughout the period of interest, are then used to forecast the normal returns in the event window. This, however, is applicable only if the individual returns, $R_{i,t}$, have an insignificant weight in the overall market return, $R_{m,t}$. In our model, the individual returns consists of whole indices and in the case of Morgan Stanley's Index for USA, the return has a significant weight in the market return (which would have to be some kind of world market return). This drawback leads us to employ the alternative way to calculate normal return, namely the constant mean model. In this model, information is assumed constant and mean return is used as a proxy for Ω_t, which is then used to estimate ((3.6). Thus we use the following model to calculate normal return:

$$R_{i,t} = \overline{R_i} + \varepsilon_{i,t} \tag{3.8}$$

where $\overline{R_i}$ simply is the mean of all returns for stock index *i* in a certain estimation window (see below). This can be compared to (3.7) where α is equal to $\overline{R_i}$ and β is equal to zero. Consequently the mean of the daily return for each separate index is calculated and assumed to be the return if the event hadn't taken place. The values of $R_{i,t}$ are gathered during an *estimation window*. We have chosen a window length of twelve months, partly due to recommendations by Peterson (1989), and partly to obtain a robust mean, deprived of seasonal effects. All event days have been excluded from the estimation window. As noted in Section 3.1 also all non trading days have been removed from the data and thus the number of days included in an estimation window can vary from event to event, depending on holidays. An outline of our windows is depicted in Figure 3.1.

Measuring and testing abnormal returns: The abnormal return is defined as

$$\varepsilon_{i,t} = R_{i,t} - E\left[R_{i,t} \middle| \Omega_t = \overline{R_{i,e}}\right] \tag{3.9}$$

Using $\overline{R}_{i,e}$ to estimate the normal performance for a specific stock index *i* and a specific event *e*, we calculate the abnormal return and test for statistical significance.

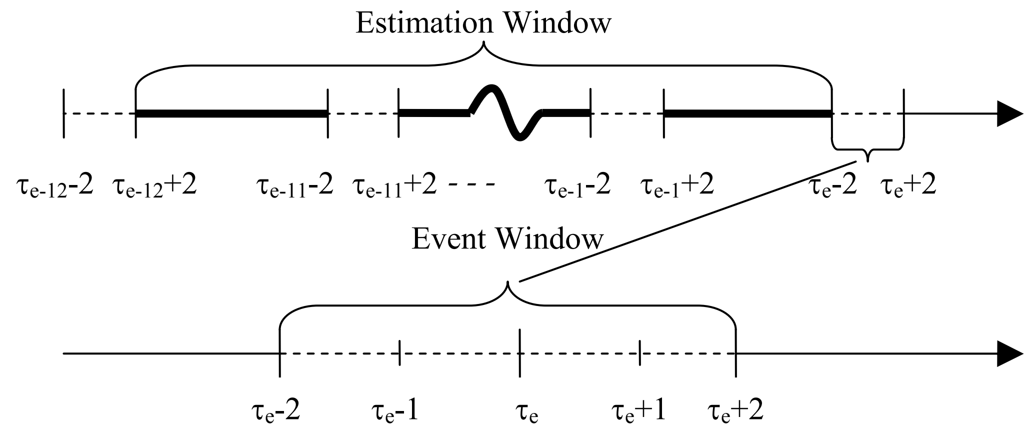

Figure 3.1 τ_e is the time for event *e*, τ_{e-1} is the time for the previous event, and so on. Depicted in the upper part of the figure is a schematic picture of the estimation window (marked with a bold line) with the event windows removed. In the lower part of the figure, the current event window is depicted.

3.3.1 Abnormal returns

Abnormal returns are calculated by comparing the actual return to the normal performance. As normal performance the return from the constant mean model in (3.8) is used. Thus the abnormal return is calculated as

$$AR_{i,\tau_e+t} = R_{i,\tau_e+t} - \overline{R}_{i,e}, \tag{3.10}$$

where $t = -2,\dots,2$ and τ_e is the time for event e.

The abnormal returns are calculated for each time t so that (3.8) is a vector of five abnormal returns, for each event e. To generate mean abnormal return across all n events we calculate the arithmetic mean of all abnormal returns vertically for each day in the event window,

$$\overline{AR}_{i,t} = \frac{1}{n}\sum_{e=1}^{n} AR_{i,\tau_e+t}, \tag{3.11}$$

3.3.2 Cumulative Abnormal Returns

It is in many cases of interest to examine the cumulative effect of a particular event, i.e., summing the mean abnormal returns calculated in (3.11) over a certain time period inside the event window. This is also of interest in our study because (3.11) perhaps doesn't yield significant abnormal returns for individual days, but may yield significant cumulative effect for a certain time period. Therefore, in addition to computing (3.11) for days $t=-2,\dots,2$, we also choose to evaluate mean Cumulative Abnormal Return, $\overline{CAR}(t_1,t_2)$, which is defined as,

$$\overline{CAR}_i(t_1,t_2) = \sum_{t=t_1}^{t_2} \overline{AR}_{i,t}. \tag{3.12}$$

Our primary interest is to calculate (3.12) for the time period after the event, i.e., $t_1=0$ and $t_2=1$ or 2 to examine if excess returns are at hand.

3.4 Hypothesis testing

In order to establish if significant mean (cumulative) abnormal return is present for a specific stock index *i*, we conduct hypothesis testing. First we define a null hypothesis,

$$H_0 : \overline{CAR}_i(t_1, t_2) = 0,$$

and then our alternative hypothesis

$$H_1 : \overline{CAR}_i(t_1, t_2) \neq 0.$$

In words, we assume that the true mean cumulative abnormal return under our null hypothesis is zero. If we obtain a value "sufficiently" different from zero, either positive or negative, we *reject* the null hypothesis in favour of the alternative hypothesis. Under the null hypothesis we create a test variable that follows a Student's t distribution with *n-1* degrees of freedom:

$$tval = \frac{\overline{CAR_i}(t_1, t_2)}{se\left(\overline{CAR_i}(t_1, t_2)\right)} \sim t_{n-1},$$

where n is the size of the sample, in our case 49 and 130, and *se* is the *standard error* of the estimate. The standard error of the estimate is calculated as follows:

$$\begin{aligned}
se\left(\overline{CAR_i}(t_1,t_2)\right) &= \sqrt{V\hat{a}r\left(\overline{CAR_i}(t_1,t_2)\right)} = \sqrt{V\hat{a}r\left(\frac{1}{n}\sum_{j=1}^{n} CAR_{i,j}(t_1,t_2)\right)} \\
&= \sqrt{\frac{1}{n^2}\sum_{j=1}^{n} V\hat{a}r\left(CAR_{i,j}(t_1,t_2)\right)} = \sqrt{\frac{1}{n^2}\, n \cdot V\hat{a}r\left(CAR_{i,j}(t_1,t_2)\right)} \\
&= \sqrt{\frac{1}{n}\frac{1}{n-1}\sum_{j=1}^{n}\left(CAR_{i,j}(t_1,t_2) - \overline{CAR}_i(t_1,t_2)\right)^2} \\
&\approx \sqrt{\frac{1}{n^2}\sum_{j=1}^{n}\left(CAR_{i,j}(t_1,t_2) - \overline{CAR}_i(t_1,t_2)\right)^2}
\end{aligned}$$

We assume that the variance is constant and returns are uncorrelated between events. Using a 5% two-tailed test we wind up with the following *critical* values for tval:

$|c_{48}| \approx 2.01$ for the sample with 49 observations, and

$|c_{129}| \approx 1.98$ for the sample with 130 observations.

This means that, if the absolute value of *tval* is larger than the critical value for either sample, we reject the null hypothesis. When this happens we denote *tval* as *statistically significant*.

4 Result

Our results for this study are presented country by country, where the analysis of each country is divided into three branches. In the first branch for each country, we cover our results when events are categorized according to the true market expectations, using only a sample of 49 observations. Our decomposition into subgroups yields 38 positive events and 11 negative events. Due to the somewhat small quantity of data (especially for the negative group), we do not expect any statistical significance here. Finally, the last two branches for each country utilize exactly the same stock index data, using a sample of 130 observations, and differ only in the model used to categorize the events. Using the model inspired by Boyd *et al.* we arrive at 63 positive events and 67 negative events, and using previous unemployment as forecast yields 89 positive events and 41 negative events. Included in the positive groups are also the events where the forecast matches the real unemployment rate.

But first, a short presentation of the unemployment rate progress during the period of interest.

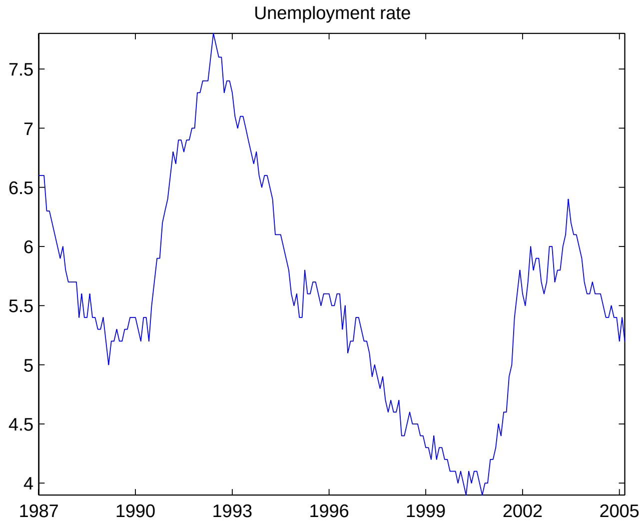

Figure 4.1 Unemployment rate for USA, January 1987 to March 2005.

The US unemployment rates in Figure 4.1 clearly depict how unemployment rate follow business cycles, contraction in the early nineties and after the IT-boom with a long period of expansion in between.

All indices used in this thesis have kurtosis in the magnitude of six; this should be compared to a Gaussian distribution with kurtosis of three. A high kurtosis implies a “fatter” or “heavier” tail in the daily return distribution.

For every country the mean abnormal return for each day in the event window and for each forecast model is plotted below. If statistical significance at the 5 percent level for mean abnormal return is present for a certain day this is marked by a filled circle.

4.1 USA

In the time period of interest, the US market has shown a positive trend except for the three years succeeding the IT-boom.

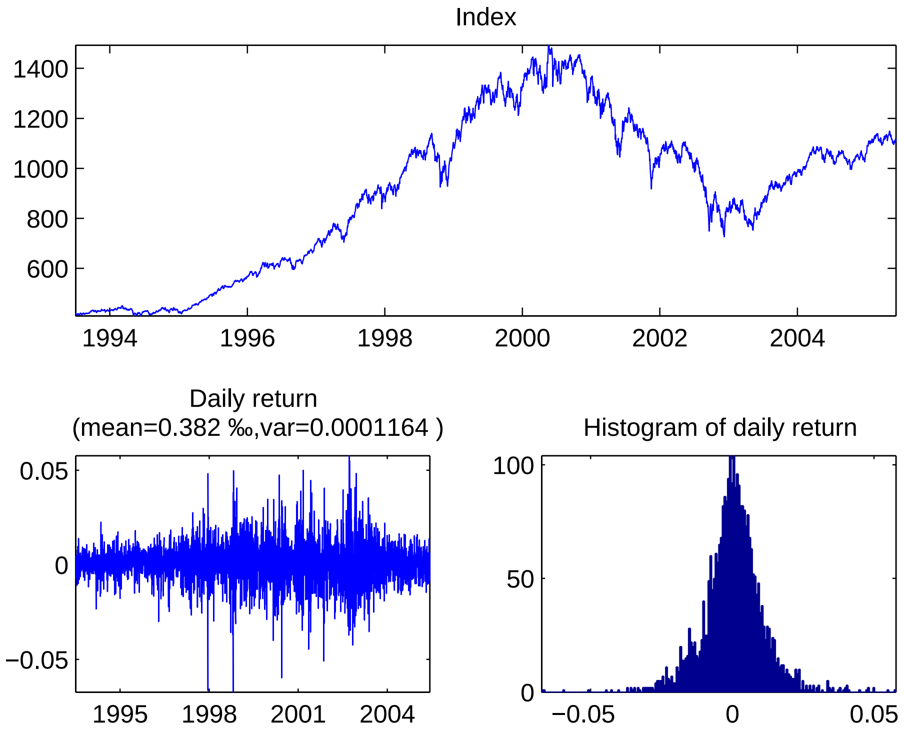

Figure 4.2 Upper, Morgan Stanley index of the US market is depicted. Lower left, daily returns in per cent, looks like Gaussian noise. Lower right, histogram of the daily returns; the Gaussian distribution is discarded due to heavy tails.

Forecast by market

When analyzing the excess returns on the US market using real market expectations of the unemployment rate to categorize the events; some peculiar and confusing results stands out. One explanation to the peculiar results in day *-1*, depicted in Figure 4.3 below, is that the information is revealed to the market prior to the press release, another possible explanation is that the result for day *-1* is based on speculative behaviour. N.B. we didn't expect any significance in the forecast by the market, but here we have statistical significance at event day *-1*. See Appendix C for CARs and significance.

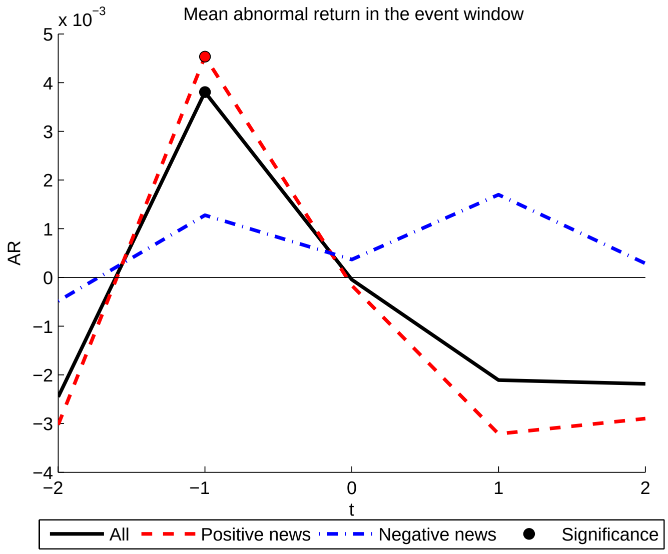

Figure 4.3 The mean abnormal return on the US market categorized by the market expectations.

Forecast model

Having analyzed the US market with the market expectations we turn to the model used by Boyd *et al.* As we can see the model separate positive and negative news but not to the extent shown in the previous forecast and it's noteworthy that the model assign negative news higher mean AR. Without categorizing the events we get a statistical significant mean AR in Figure 4.4, however, it is moderate though.

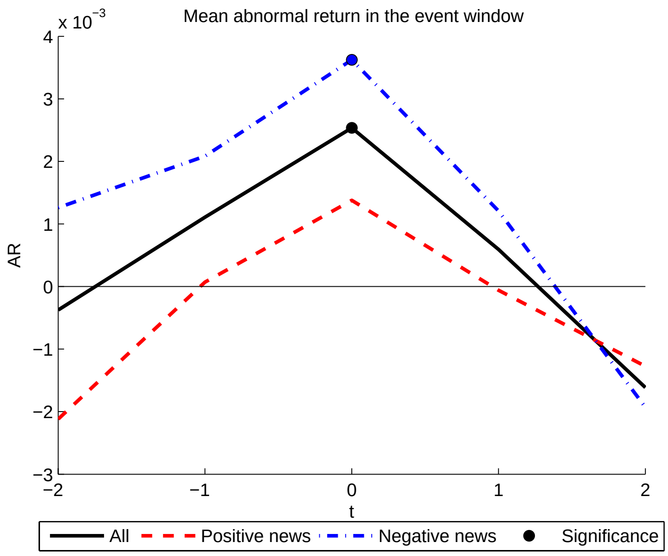

Figure 4.4 The mean abnormal return on the US market categorized by the model used in Boyd *et al.*

Forecast based upon previous unemployment rates

In Figure 4.5 we can clearly see that the conditions are the same, when employing the least complex forecasting method. The big difference in the result, when previous unemployment rates are used for categorization compared to the preceding model, is that this one gives statistical significance at day *-1*, exactly the same way as the market forecast did, but this one is for negative news, nevertheless, the mean AR is not of the same magnitude as in Figure 4.3.

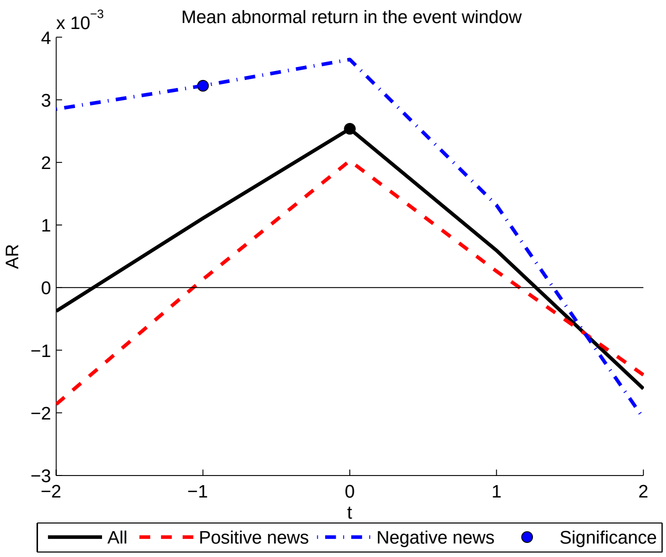

Figure 4.5 The mean abnormal return on the US market categorized by the difference in the unemployment rate from the previous month.

4.2 Germany

The German market follows the same business cycle as the US market, but, the German market is somewhat more volatile.

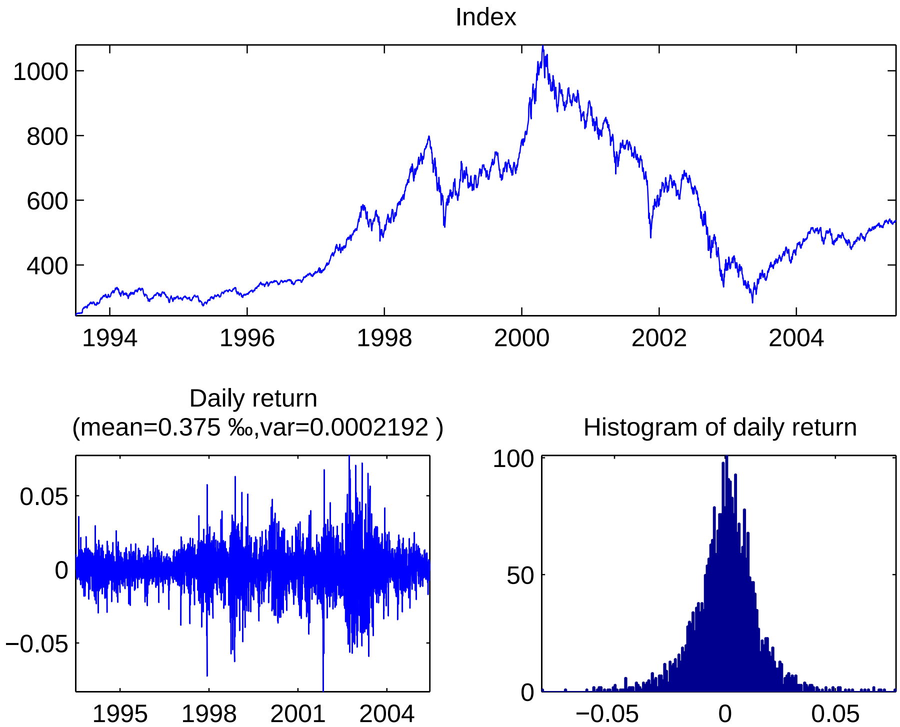

Figure 4.6 Upper, Morgan Stanley index of the German market is depicted. Lower left, daily returns in per cent, looks like Gaussian noise. Lower right, histogram of the daily returns; the Gaussian distribution is discarded due to heavy tails.

Forecast by market

At a first visual analysis of the mean AR on the German market in Figure 4.7, we notice that the plot is similar to the mean abnormal return on the US market, Figure 4.3. In this figure we find peculiar results as well, analogous to the US market, we have the peak at day *-1*, we also find some odd significance at day *-2*, and we have not found any reasonable explanation to this dip. Hence the only statistical significant values are at day *-2* and they are unexplained so we cannot reject the null hypothesis regarding spill over effects.

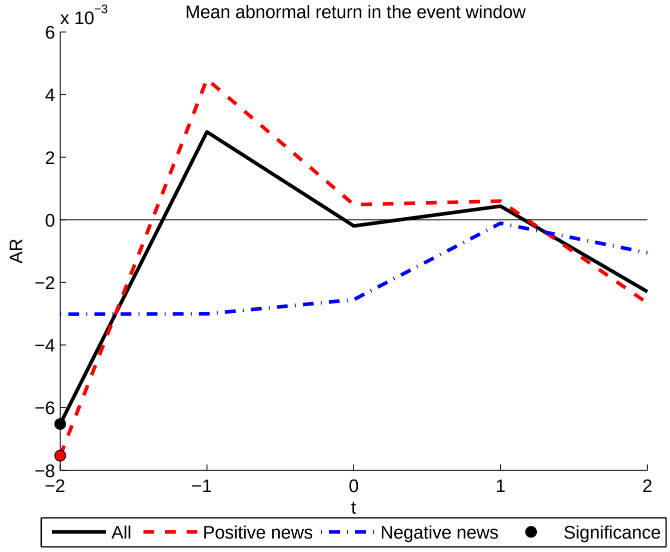

Figure 4.7 The mean abnormal return on the German market categorized by the market expectations.

Forecast model

The German market continues to show the same patterns as the US market, negative news on top, for the corresponding categorization method (see Figure 4.8 and Figure 4.4). Between day *0* and day *1*, we can see an almost flat tendency; this might be an effect due to the time difference of six hours, and thus the US unemployment rates affect the German market during two business days, even though we have a significant mean AR on day *1*.

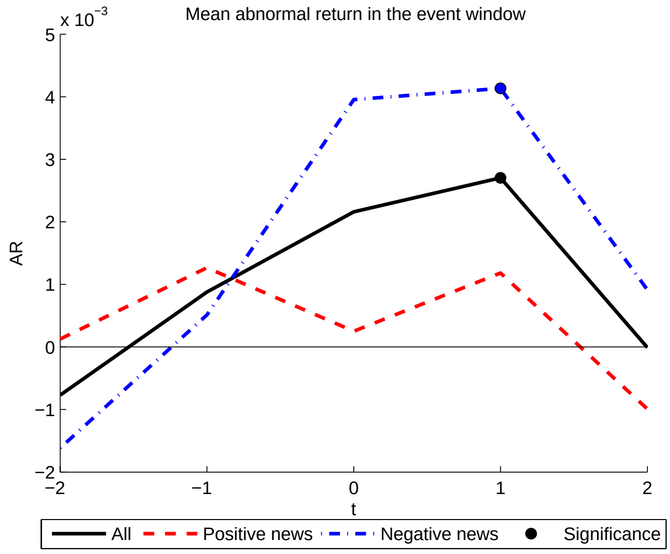

Figure 4.8 The mean abnormal return on the German market categorized by the model used in Boyd *et al.*

Hence the affect is stretched out over two days and we get statistical significant CARs from day *-1* to day *2*, see Appendix C for the full CAR-matrices. Consequently there are spill over effects on the German market.

Forecast based upon previous unemployment rates

The uncategorized AR, depicted as “All” in both in Figure 4.8 and Figure 4.9, show the same pattern—lagged one day compared to the US market. Otherwise the negative-, and positive news plots doesn’t show any similarities with the corresponding plots for the US market, Figure 4.5. If we compare the negative-, and positive news plots for the two different forecasting models we see the same pattern in Figure 4.8 and Figure 4.9, likewise this method gives statistical significant CAR for the days *-1* to day *1*.

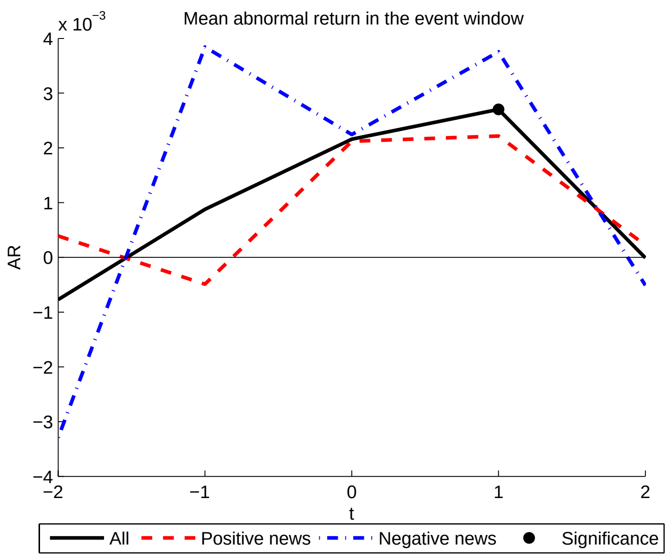

Figure 4.9 The mean abnormal return on the German market categorized by the difference in the unemployment rate from the previous month.

4.3 UK

The UK market show the same the tendencies as the US market, however, the UK market is slightly less volatile compared to the US market.

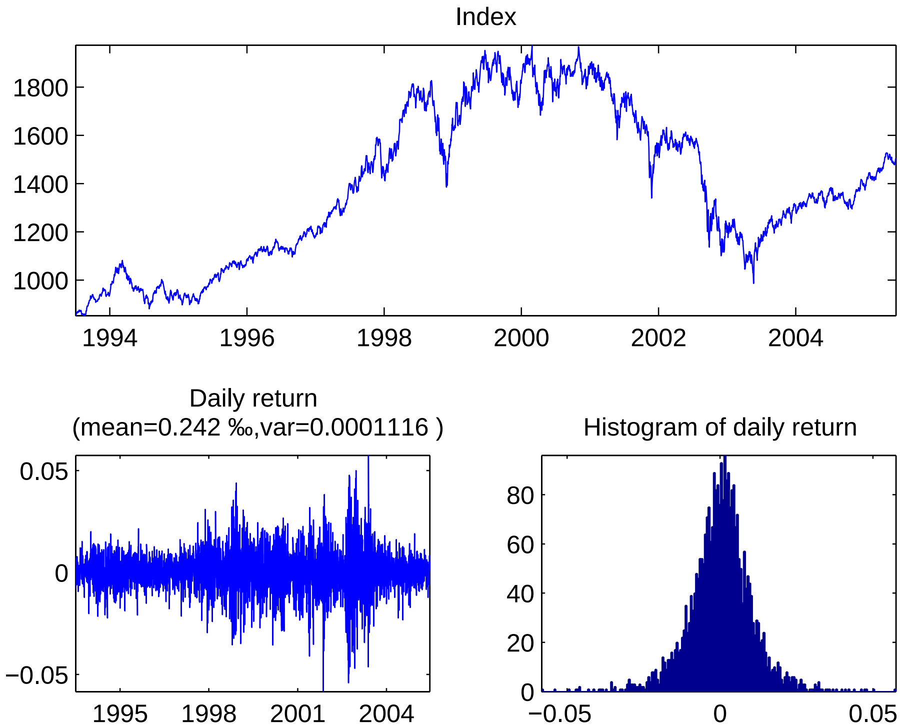

Figure 4.10 Upper, Morgan Stanley index of the UK market is depicted. Lower left, daily returns in per cent, looks like Gaussian noise. Lower right, histogram of the daily returns; the Gaussian distribution is discarded due to heavy tails.

Forecast by market

The UK market is not different from the previous two markets—peculiar and odd behaviours. For negative news the UK market demonstrates some kind of schadenfreude when the market forecast is applied for day *0*, although this isn't statistically significant. Finally we again find the odd statistical significance for day *-2*.

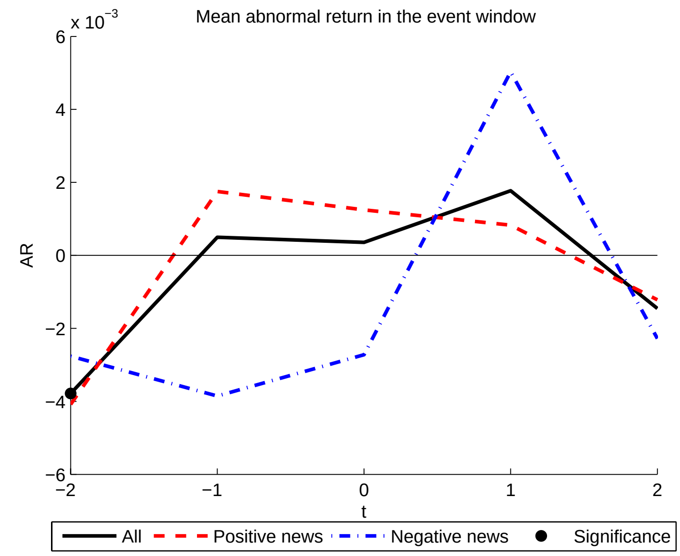

Figure 4.11 The mean abnormal return on the UK market categorized by the market expectations.

Forecast model

When the model in Boyd *et al.* is employed to the UK market we notice that the market follows the same pattern as in Figure 4.11, i.e., the effect induced by the unemployment rate press release is lagged one day, however, with this model we get statistical significance on the AR for negative news as well as for CAR, day *0* to day *1*, though it's moderate.

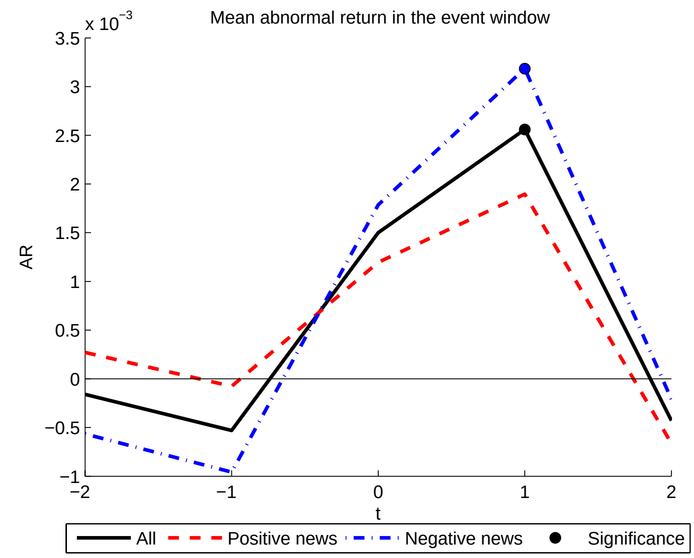

Figure 4.12 The mean abnormal return on the UK market categorized by the model used in Boyd *et al.*

Forecast based upon previous unemployment rates

This final plot, Figure 4.13, for UK doesn't surprise us at all, the major effect is lagged one day, and finally we have statistical significance for AR at day *1* for positive news and for CAR as well for day *0* to day *1*.

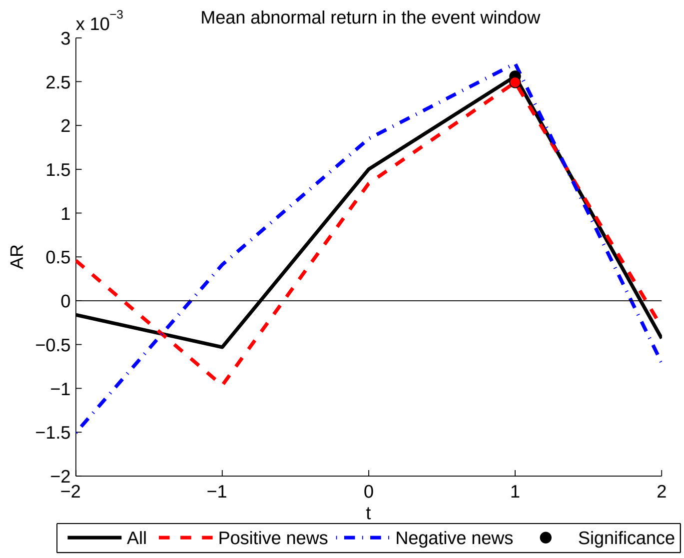

Figure 4.13 The mean abnormal return on the UK market categorized by the difference in the unemployment rate from the previous month.

4.4 Japan

The progress on the Japanese market look totally different to the other indices, the Japanese market has a negative mean return and a high volatility compared to the US market. Since the Japanese market doesn't appear to follow the same business cycles as the other markets during the time period of interest, we expect to have different results from the Japanese market.

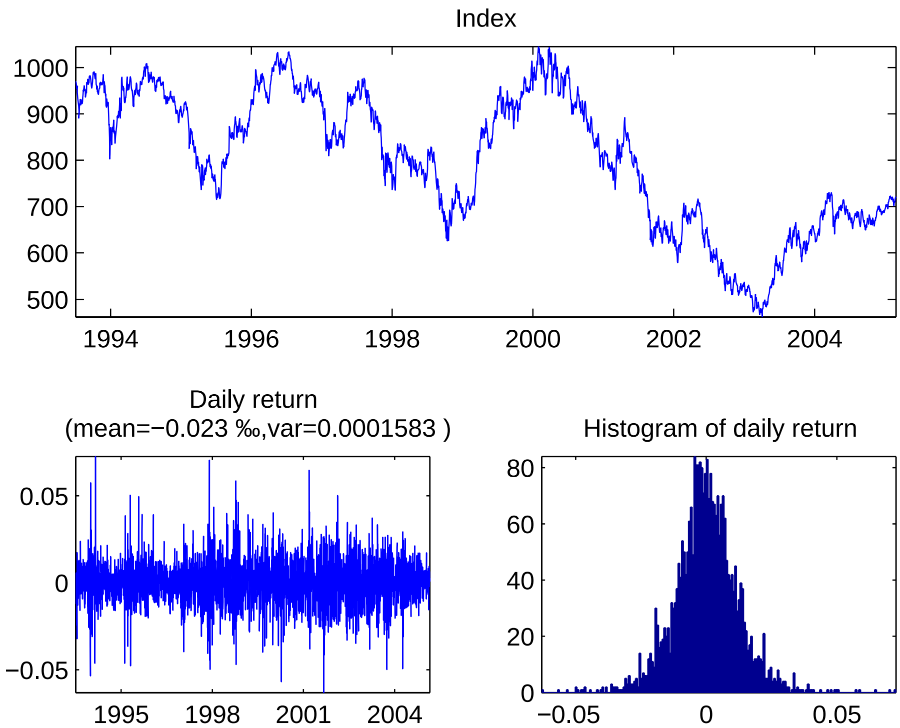

Figure 4.14 Upper, Morgan Stanley index of the Japanese market is depicted. Lower left, daily returns in per cent, looks like Gaussian noise. Lower right, histogram of the daily returns; the Gaussian distribution is discarded due to heavy tails.

On the Japanese market the different time zones should lag the effects from the unemployment rate press release a whole day, if the US unemployment rates affect the Japanese market we expect the effect from day 0 to occur on day 1 on the Japanese market due to the 15 hour time difference.

Forecast by market

The strike of peculiar results for the forecast made by the market continues—the Japanese market doesn't follow the previous patterns, instead negative news generates excess returns, although not significantly. As we can se in Figure 4.15, the Japanese market show of some kind of schadenfreude in the whole event window. The statistical significance for positive news at day -1 is equivalent to the peculiar results from the other countries at day *-2*. None of the days are significant for negative news; however, note the fairly big area below the negative curve, i.e., CAR for day *-2* to *0*, is 1.4 percent and although not significant, it's fairly close.

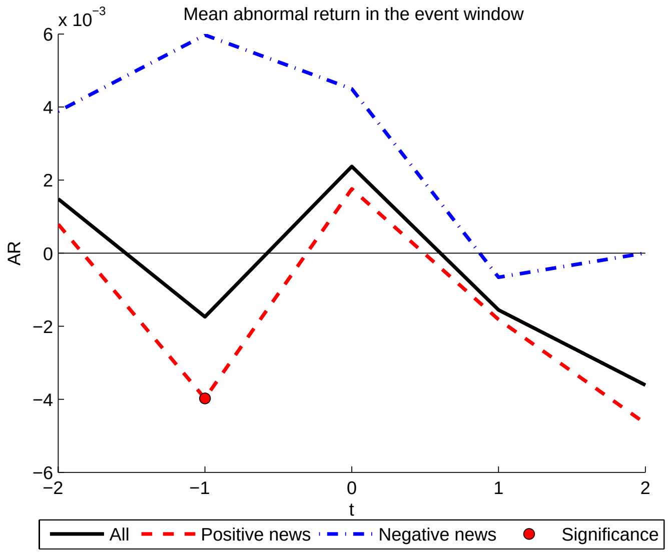

Figure 4.15 The mean abnormal return on the Japanese market categorized by the market expectations.

Forecast model

Having noticed a different pattern in the previous plot for Japan compared to the other countries, therefore we are not surprised when Japan shows no reaction at all to the unemployment rate press releases. We don't have any indications on what might be the cause of this lack of reaction. It could be an effect of the structural problems in the Japanese economy during the 90's, it is only speculations though.

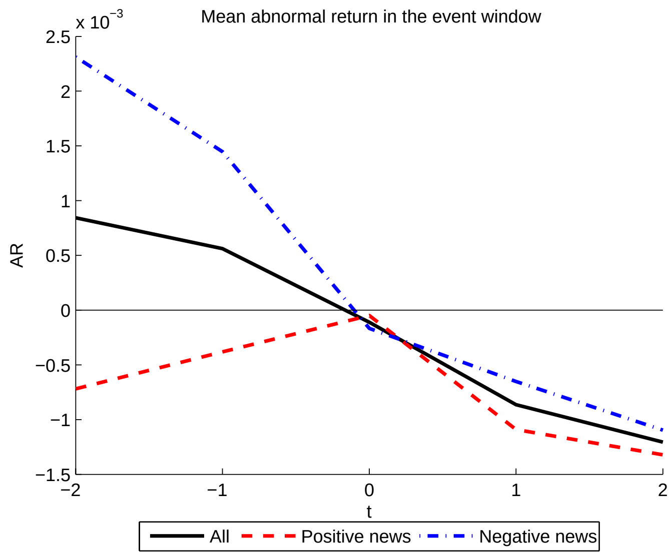

Figure 4.16 The mean abnormal return on the Japanese market categorized by the model used in Boyd *et al.*

Forecast based upon previous unemployment rates

As we have mentioned in the analysis of the other countries the negative- and positive news plots are similar in Figure 4.16 and Figure 4.17 respectively. There is not a single indication for spill over effects on the Japanese market.

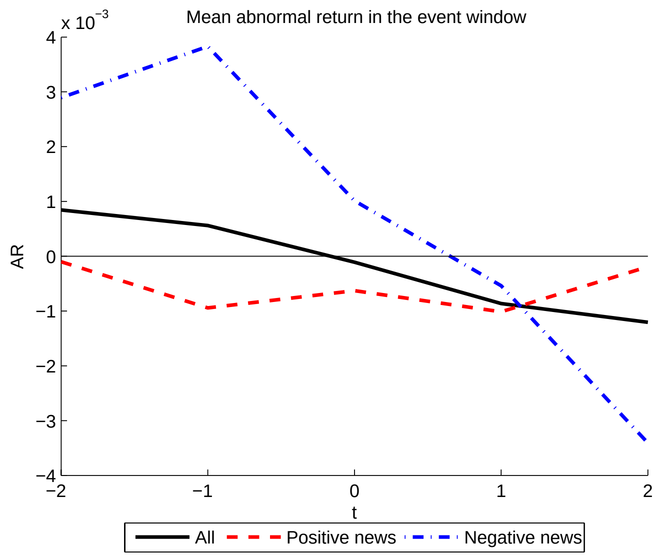

Figure 4.17 The mean abnormal return on the Japanese market categorized by the difference in the unemployment rate from the previous month.

4.5 France

France shows the same pattern as the other markets, with the exception o Japan. The French market is more volatile than the US market, but less so than the German market.

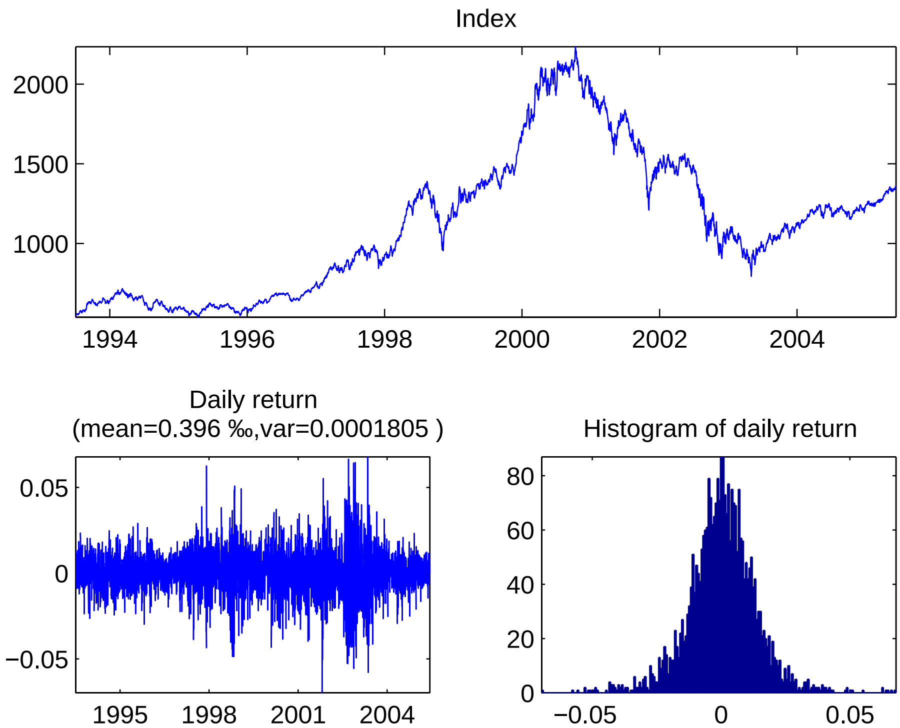

Figure 4.18 Upper, Morgan Stanley index of the French market is depicted. Lower left, daily returns in per cent, looks like Gaussian noise. Lower right, histogram of the daily returns; the Gaussian distribution is discarded due to heavy tails.

Forecast by market

For the French market we are back on track with peculiar results, a non statistical significant market reaction on day *-1*, and a huge negative mean AR for positive news on day *-2*.

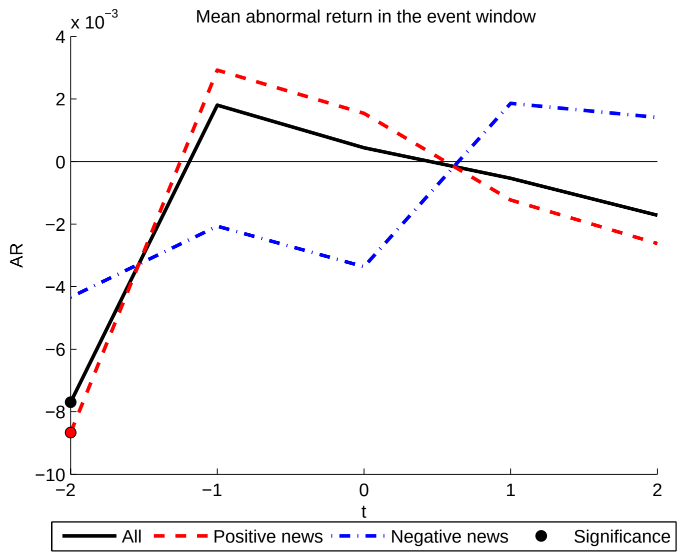

Figure 4.19 The mean abnormal return on the French market categorized by the market expectations.

Forecast model

When employing the forecast model for the AR on the French market we get statistical significance for positive news as well as for all news at day *0*, for day *1* we get significance for negative news. It is interesting to see the discrepancy at day *1* for positive and negative news respectively. Finally there is one statistical significant CAR for negative news, which is obvious from Figure 4.20, day *0* to day *1*.

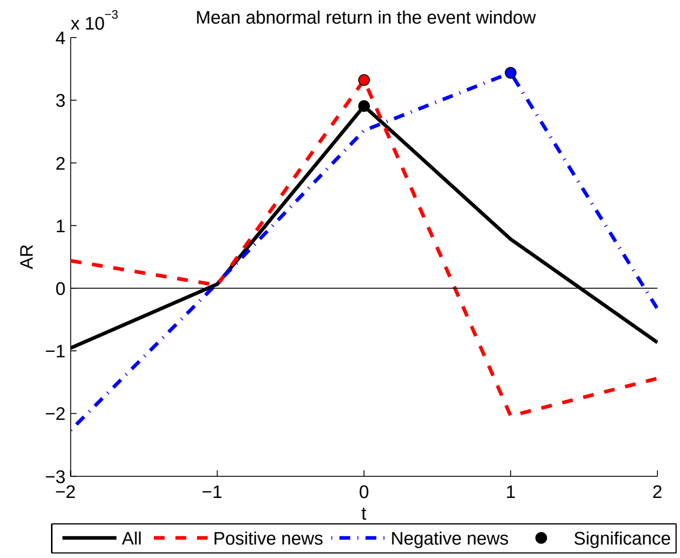

Figure 4.20 The mean abnormal return on the French market categorized by the model used in Boyd *et al.*

Forecast based upon previous unemployment rates

This method continues to show a similar behaviour to the previous model, but now only for positive news. For negative news this model shows the same pattern as for Germany. AR for positive news at day 0 is significant, but we find no statistical significant CARs.

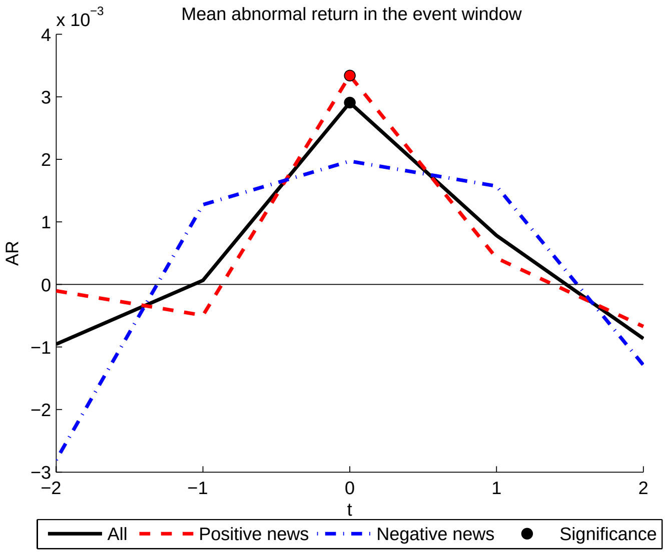

Figure 4.21 The mean abnormal return on the French market categorized by the difference in the unemployment rate from the previous month.

4.6 Sweden

The Swedish market mimics the business cycles of the western world, although more accentuated. This market is without doubt the most volatile market in our study. It's noteworthy to see that the index increased by a factor 12 between late 1993 and 2000.

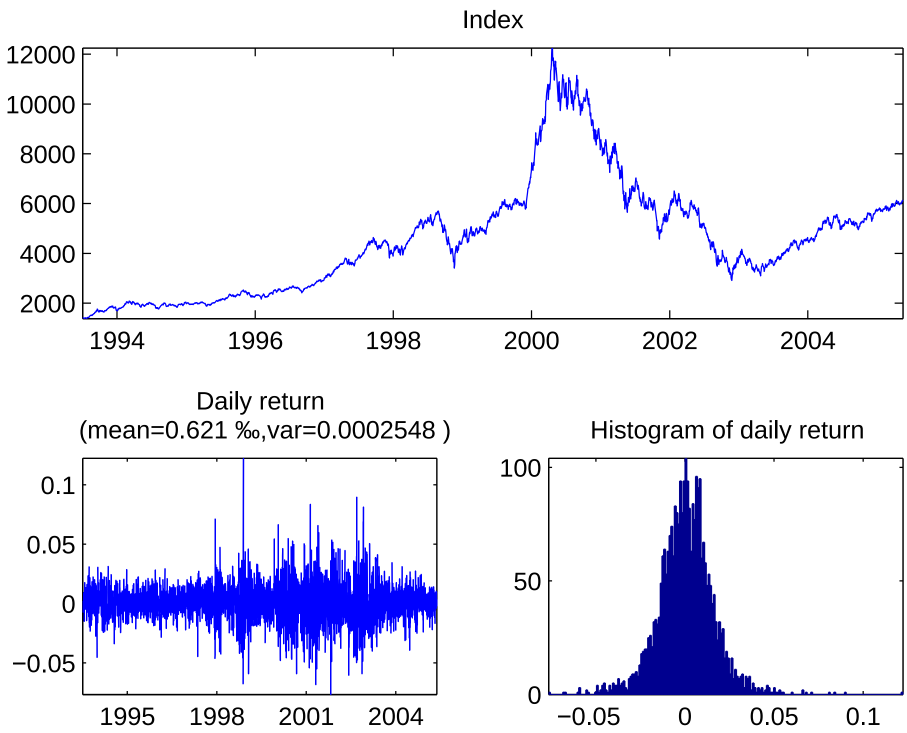

Figure 4.22 Upper, Morgan Stanley index of the Swedish market is depicted. Lower left, daily returns in per cent, looks like Gaussian noise. Lower right, histogram of the daily returns; the Gaussian distribution is discarded due to heavy tails.

The Swedish market is the only small market in our survey; therefore it is interesting to see whether the effect is different on the Swedish market compared to more liquid markets.

Forecast by market

Even on this fairly small market we spot this odd negative AR on day *-2*, but it is not significant. No other days are significant in Figure 4.23 since the somewhat small amount of data; the major effect is on day *0* for positive news, thus resulting in a statistical significant CAR for day -1 to day *0*.

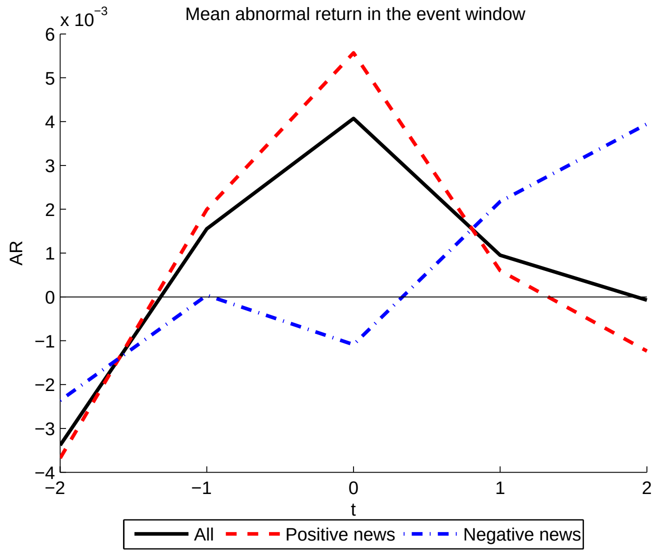

Figure 4.23 The mean abnormal return on the Swedish market categorized by the market expectations.

Forecast model

In contradiction to Figure 4.23, we have statistical significance for several days when employing the model used by Boyd *et al.* Contrary to other markets, France excluded, AR for positive news is higher than for negative news. When analysing the CARs in Appendix C we have numerous significant CARs for all news and for negative news. The CARs for negative news are in the magnitude of 1 percent which we have to regard as a very high return.

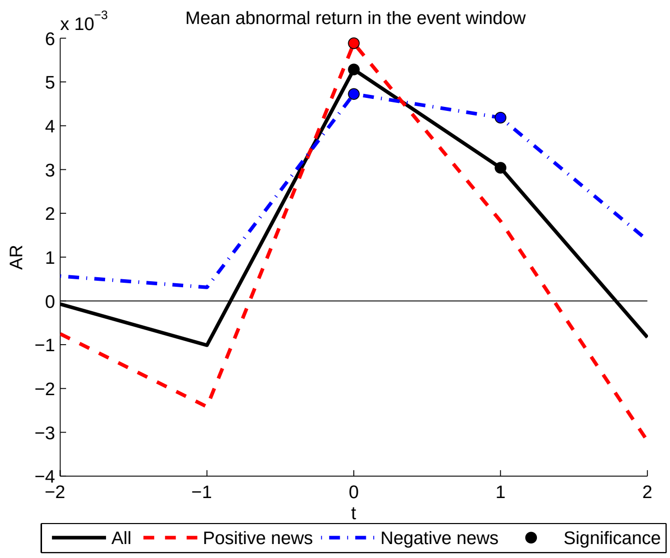

Figure 4.24 The mean abnormal return on the Swedish market categorized by the model used in Boyd *et al.*

Forecast based upon previous unemployment rates

The method of categorizing the events using previous unemployment rate, appears in the same fashion as the other countries (not counting France), with negative news generating higher AR than positive news. Significant CARs for negative news are higher than for positive news, which is in accordance to previous results. This method generates CARs in the same magnitude as the forecast method used by Boyd *et al.* As a final note, we conclude that the Swedish market is affected by the US unemployment rate and therefore spill over effects are present.

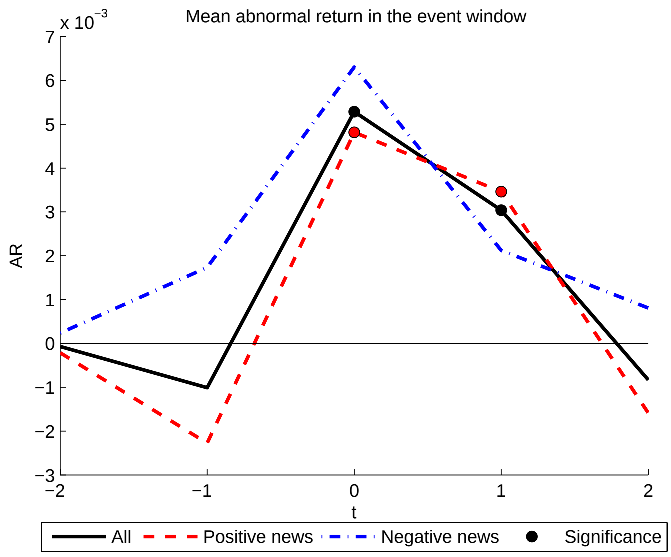

Figure 4.25 The mean abnormal return on the Swedish market categorized by the difference in the unemployment rate from the previous month.

5 Conclusions

The six different markets we have analyzed yields widely different results. The most significant results emerged from Sweden and we interpret this as a small economy like the Swedish is more sensitive to changes in American unemployment and generally more dependant on the activities of larger, more powerful economies, e.g., USA, Germany, and, UK. In the following discussion, Japan is excluded, because of the deviating, inconsistent, and insignificant behaviour.

The *market forecast* model shows that positive news is positively correlated to abnormal return in all. Also positive news is followed by an adjustment downwards in the days succeeding the day *0*. At day *1* or *2* the negative news plot crosses the positive. We interpret this as positive news tends to be overpriced initially and is thus corrected downwards the following days. Negative news doesn't appear to affect the market to the same extent—the plot is relatively flat and mostly negative. However, negative news always generates higher AR on day *1* than on day *0*. The validity of investigating the days before the event day for either positive or negative news can be questioned. How can the market react differently to future positive or negative information when they shouldn't be able to anticipate the outcome? If speculative behaviour is present, such activity should be noticeable in the aggregate plot as well as the positive and negative news plot which should behave the same way. As can be seen, they do not behave the same way which leads to a suspicion that information is leaked to, at least part of, the market before the event has taken place. We conclude that weak spill over effects on the event day can be ascertained for all markets, but the most dominating effect is the speculative, present on the days before the event day. The only statistically significant result (apart from the odd significance at day *-2*) is the peak at day *-1* for the US market, but we suspect that if a larger sample had been used the same results would emerge significantly. A summary of statistical significances on the different markets is presented in Table 5.1. A few significant CARs for positive and negative news are excluded, because they belong to days prior to the event and this information can only be used by insiders.

Market Expectations			
	All (%)	**Positive (%)**	**Negative (%)**
USA	CAR(-1,-1)=0.380(2.735)	CAR(1,2)=-0.611(-2.208)	-
GER	CAR(-2,-2)=-0.652(-2.576)	-	-
UK	CAR(-2,-2)=-0.379(-2.097)	-	-
JPN	-	-	-
FRA	-	-	-
SWE	-	-	-

Table 5.1 Summary of relevant statistical significances using the market forecast model. The calculated t-statistic for each CAR is in parenthesis.

By using a larger sample of 130 events from July 1994 to April 2005 we get more significant results. Looking at just the aggregate plot of AR, we have positive significance on day *0* or day *1* for all markets. This is interesting, because it implies that, without knowing the outcome of the event, an investor could generate excess returns by going long in a portfolio similar to the index in the end of day *-1* and going short in the end of day *1*. This result was not expected as we assumed that positive and negative news would cancel each other out and yield insignificant aggregate results. This was the reason we tried to divide the events into two subgroups using the forecast models (3.2) and (3.4). Being blunt, one could jump to the conclusion that all markets thus are inefficient. However, in the real world there are transaction costs that probably would cancel out the rather small excess returns, the exception being the Swedish market where the excess return is almost twice as big compared to the other markets.

Our attempt to categorize events into positive news and negative news using forecast models (3.2) and (3.4) yields inconclusive results. The forecast model à la Boyd *et al.* in all cases, except for Sweden and France, yields similar results compared to using previous unemployment rate as our forecast model. This could be because both forecast models have previous unemployment rate as an explanatory variable. The days with significant values for negative news occur at the same days as significance for aggregate results, with approximately the same significance. If the two subgroups were composed in a good fashion, they would yield significance for positive news as well. Noteworthy is that negative news in these two forecast models yields higher AR than positive news do. This is contradictory to the results using the real market forecasts, which leads us to consider that our models don't do the job well of forecasting anticipated unemployment rates. Nevertheless we present a summary of significant results for the two models in Table 5.2 and Table 5.3.

Boyd *et al.*			
	All (%)	**Positive (%)**	**Negative (%)**
USA	CAR(-1,1)=0.424(2.746) CAR(0,0)=0.254(2.417) CAR(0,1)=0.313(2.206)	-	CAR(0,0)=0.362(2.302) CAR(0,1)=0.483(2.457)
GER	CAR(-1,1)=0.574(2.462) CAR(0,1)=0.486(2.492)	-	CAR(0,1)=0.809(2.833) CAR(0,2)=0.900(2.174)
UK	CAR(0,1)=0.406(2.981)	-	CAR(0,1)=0.497(2.617)
JPN	-	-	-
FRA	CAR(0,0)=0.291(2.344) CAR(0,1)=0.369(2.122)	CAR(0,0)=0.332(2.368)	CAR(0,1)=0.595(2.225))
SWE	CAR(0,0)=0.529(3.296) CAR(0,1)=0.833(3.898)	CAR(0,0)=0.588(2.649) CAR(0,1)=0.771(2.454)	CAR(0,0)=0.472(2.049) CAR(0,1)=0.891(3.066) CAR(0,2)=1.030(2.661)

Table 5.2 A summary of relevant statistical significances for the forecast model used by Boyd *et al.* The calculated t-statistic for each CAR is in parenthesis.

Previous unemployment			
	All (%)	**Positive (%)**	**Negative (%)**
USA	CAR(-1,1)=0.424(2.746) CAR(0,0)=0.254(2.417) CAR(0,1)=0.313(2.206)	-	CAR(0,1)=0.496(2.068)
GER	CAR(-1,1)=0.574(2.462) CAR(0,1)=0.486(2.492)	-	-
UK	CAR(0,1)=0.406(2.981)	CAR(0,1)=0.383(2.421)	-
JPN	-	-	-
FRA	CAR(0,0)=0.291(2.344) CAR(0,1)=0.369(2.122)	CAR(0,0)=0.334(2.408)	-
SWE	CAR(0,0)=0.529(3.296) CAR(0,1)=0.833(3.898)	CAR(0,0)=0.482(2.713) CAR(0,1)=0.828(3.324)	CAR(0,1)=0.843(2.066)

Table 5.3 A summary of relevant statistical significances for the forecast model based on previous unemployment rate. The "All" column is the same as in Table 5.2. The calculated t-statistic for each CAR is in parenthesis.

As in the case of market forecasts a few significant CARs for positive and negative news are excluded, because they belong to days prior to the event and this information can only be used by insiders.

An interesting point is that if we calculate MSFE according to (3.5) we find that the model by Boyd *et al.* produces the lowest value, followed by the previous unemployment rate model. Thus, even if the two models are unable to estimate the market forecasts, they are better[4] than the market in forecasting the real unemployment rate. A closer look shows that the market on average has pessimistic view of the unemployment rate (which also can be seen in the distribution shown in Chapter 1), while the two other models on average are somewhat optimistic in their forecasts. This is the reason that the positive, and negative news curves are swapped in the two latter models relative to the market forecast model.

If the unanticipated information is priced instantaneously, then the market is efficient. As we have seen, more or less, there is an effect prior to the press release on all markets, which could depend on speculative behaviour. All markets in our survey except for the Japanese market indicate spill over effects, some of the markets with statistical significance.

On the Swedish market it is obvious that there is a possibility to generate excess return systematically, even without knowing the outcome of the press release. Consequently the Swedish market can not be regarded as efficient yet.

5.1 Weaknesses

The major problem with the Boyd *et al.* model is that it is constructed to forecast the unemployment rate change. Our aim with this model is to estimate the market forecast, in order to estimate the unanticipated unemployment rate; and therefore, we get different results with the market forecast and the Boyd *et al.* model respectively.

When we categorize events into different subgroups, using the market forecast model and the previous unemployment model, several forecasts matches the real unemployment rate. In this study these events are included in the positive news subgroup. This choice was arbitrary and thus these events could just as well have been placed in the negative news subgroup or in a separate group. Using a separate group, a large enough sample could verify if all known information is incorporated in the stock indices or not. That is, no significant results should arise

[4] By ”better” we mean closer in absolute terms to the real unemployment rate.

in conjunction with unemployment rate press releases if the market is efficient, since only unanticipated information should induce an adjustment in equity prices.

A reservation to our result is that events exclusively occur on Fridays. Our estimated normal return is the mean of every non-event window day a year back. We have not taken into account if Fridays have different stock return than other week days. This could be remedied by creating our estimated normal return based on only non-event Fridays a year back. This estimated value should then only be used as normal return for the event day. The previous day should only utilize Thursdays in the estimation window, and so on. This approach would alleviate the potential problem of weak day effects. As noted in the results we get odd significant AR on day *-2* for several markets. One explanation could be a possible Wednesday effect.

5.2 Future research

A different way to conduct the study of spill over effects could be by using a regression of real market returns on the unanticipated unemployment rate, for each day in the event window. Boyd *et al.* utilize this model, in addition to taking the current state of the economy into account. This way no normal return has to be estimated and therefore one less source of error is present.

Our most intriguing result is that the Swedish market doesn't appear to be efficient. It would be interesting to know if the Swedish market also exhibit inefficient behaviour to other macroeconomic variables and also if other markets of the same size as the Swedish, show similar inefficiency.

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Appendix A Derivations

A.1 Gordon's model—infinite sum

$$P_t = \sum_{i=1}^{\infty} \frac{D_t (1+g)^i}{(1+r+\pi)^i},$$

Let

$$\mathrm{x} = \frac{(1+g)}{(1+r+\pi)},$$

then,

$$\begin{aligned} S_n &= D_1 x + D_1 x^2 + \ldots + D_1 x^n \\ xS_n &= D_1 x^2 + D_1 x^3 + \ldots + D_1 x^{n+1} \\ xS_n - S_n &= D_1 x^{n+1} - D_1 x \Leftrightarrow \\ S_n(x-1) &= xD_1(x^n - 1) \Leftrightarrow \\ S_n &= \frac{xD_1(x^n - 1)}{(x-1)}, \end{aligned}$$

and finally let *n* tend to infinity, then if x < 1,

$$\lim_{n\to\infty} S_n = \frac{xD_1(-1)}{x-1} = \frac{xD_1}{1-x} = \frac{\frac{(1+g)}{(1+r+\pi)} D_1}{1 - \frac{(1+g)}{(1+r+\pi)}} = \frac{(1+g)D_1}{(r+\pi)-g}.$$

Appendix B Program/MATLAB code

B.1 Date conversion

```
load dates&Index.mat
UK(:,1)=datenum(datestr(datestr(UKDate,2),1));
clear UKDate
USA(:,1)=datenum(datestr(datestr(USADate,2),1));
clear USADate
FRA(:,1)=datenum(datestr(datestr(franceDate,2),1));
clear franceDate
GER(:,1)=datenum(datestr(datestr(germanDate,2),1));
clear germanDate
JPN(:,1)=datenum(datestr(datestr(japanDate,2),1));
clear japanDate
SWE(:,1)=datenum(datestr(datestr(swedenDate,2),1));
clear swedenDate
UK(:,2)=UKIndex;
clear UKIndex
USA(:,2)=USAIndex;
clear USAIndex
FRA(:,2)=franceIndex;
clear franceIndex
GER(:,2)=germanIndex;
clear germanIndex
JPN(:,2)=japanIndex;
clear japanIndex
SWE(:,2)=swedenIndex;
clear swedenIndex
save NumDates&Index.mat

load Dates&UnempIPRate.mat
%converting to NumDates
UnempNumDate=datenum(datestr(UnempDate,1));
IPNumDate=datenum(datestr(IPDate),1);
%reordering, earliest first
tmp(:,1)=UnempNumDate;
tmp(:,2)=UnempRate;
tmp=sortrows(tmp,1);
Unemp = tmp;
tmp(:,1)=IPNumDate;
tmp(:,2)=IPRate;
tmp=sortrows(tmp,1);
IP = tmp;
Unemp(2:size(Unemp),3)=Unemp(2:size(Unemp),2)-Unemp(1:size(Unemp)-1,2);
clear UnempDate
clear UnempNumDate
clear UnempRate
clear IPDate
clear IPNumDate
clear IPRate
clear tmp
save Unemp&IP.mat

load dates&BondRate.mat
BondNumDate = datenum(bondDate(:,1),bondDate(:,2),1); %set date to the first of
each month.
Bond(:,1)=BondNumDate;
Bond(:,2)=Aaa;
Bond(:,3)=Baa;
Bond(:,4)=Tbill3M;
clear bondDate
clear BondNumDate
clear Aaa
clear Baa
clear Tbill3M
save Bond.mat
```

B.2 Hypothesis test

```
function [TextMatrix TextMatrixPos TextMatrixNeg ...
            TextMatrixPosPrev TextMatrixNegPrev ...
            TextMatrixFC TextMatrixPosFC TextMatrixNegFC]=Index(StartDate, Coun-
try, Unemp, UnempForecast, EventWindowDim, Months)
close all
Country = CleanData(Country);
MRCountry = MeanReturn(StartDate, Country, Unemp, EventWindowDim, Months);
myAR = AbnormalReturn(MRCountry, Country, EventWindowDim);
[PosAR NegAR PosARPrev NegARPrev PosARFC Ne-
gARFC]=PosNegAR(myAR,Unemp,UnempForecast);

[TextMatrix Stat]=Statistics(myAR,EventWindowDim);
[TextMatrixPos StatPos]=Statistics(PosAR,EventWindowDim);
[TextMatrixNeg StatNeg]=Statistics(NegAR,EventWindowDim);
plotAR(Stat, StatPos, StatNeg, 'Boyd',EventWindowDim,length(myAR)-1,length(PosAR)-
1,length(NegAR)-1)

%Stat=Statistics(myAR,EventWindowDim);
[TextMatrixPosPrev StatPosPrev]=Statistics(PosARPrev,EventWindowDim);
[TextMatrixNegPrev StatNegPrev]=Statistics(NegARPrev,EventWindowDim);
plotAR(Stat, StatPosPrev, StatNegPrev, 'Prev',EventWindowDim,length(myAR)-
1,length(PosARPrev)-1,length(NegARPrev)-1)

f=find(myAR(:,1)==UnempForecast(1,1));
[TextMatrixFC StatFC]=Statistics(myAR(f:end,:),EventWindowDim);
[TextMatrixPosFC StatPosFC]=Statistics(PosARFC,EventWindowDim);
[TextMatrixNegFC StatNegFC]=Statistics(NegARFC,EventWindowDim);
plotAR(StatFC, StatPosFC, StatNegFC, 'FC',EventWindowDim,length(myAR)-
1,length(PosARFC)-1,length(NegARFC)-1)


function CAR = CummulativeReturn(AR)
CAR(:,1) = AR(:,1);
for i=1:length(CAR)
    CAR(i,2) = sum(AR(i,2:end));
end


function Country = CleanData(Country)
tmp=Country(1,:);
for i=1:length(Country)-1
    if (tmp(end,2)~=Country(i+1,2)) && (Country(i+1,2)~=0)
        tmp = cat(1,tmp,Country(i+1,:));
    end
end
tmp(2:length(tmp),3) = (tmp(2:length(tmp),2)-tmp(1:length(tmp)-
1,2))./tmp(1:length(tmp)-1,2);
Country = tmp;


function CAR = CumAR(myAR,x,y,EventWindowDim)
if x<EventWindowDim(1) || y>EventWindowDim(2) || x>y
    sprintf('Incorrect index!')
else
    for i=1:length(myAR)
        CAR(i,1) = sum(myAR(i,x-EventWindowDim(1)+2:y-EventWindowDim(1)+2));
    end
end


function AR=AbnormalReturn(MR, Country, EventWindowLength)
Window = EventWindowLength(2)-EventWindowLength(1)+1;
AR(:,1)=MR(:,1);
for i=1:length(AR)
    first = find(Country(:,1)<MR(i,1),1,'last')+EventWindowLength(1)+1;
    second = first+Window-1;
    AR(i,2:Window+1) = (Country(first:second,3)-MR(i,2))';
end
```

```
function MR=MeanReturn(StartDate, Country, Unemp, EventWindowLength, Months)
begin = find(Unemp(:,1)>=StartDate,1);
MR(:,1)=Unemp(begin:end,1);
first = find(Country(:,1)>=Unemp(begin-Months,1),1)+EventWindowLength(2)+1;
second = find(Country(:,1)<Unemp(begin-Months+1,1),1,'last')+EventWindowLength(1);
EstimationArray = Country(first:second,:);
for i=1:length(Unemp)-begin+Months-1
    first = find(Country(:,1)>=Unemp(i+begin-Months,1),1)+EventWindowLength(2)+1;
    second = find(Country(:,1)<Unemp(i+begin-
Months+1,1),1,'last')+EventWindowLength(1);
    EstimationArray = cat(1,EstimationArray,Country(first:second,:));
end
for j=1:length(MR)
    firstEventDate = Unemp(find(Unemp(:,1)==MR(j,1))-Months,1);
    lastEventDate = Unemp(find(Unemp(:,1)==MR(j,1)),1);
    first = find(EstimationArray(:,1)>firstEventDate,1);
    second = find(EstimationArray(:,1)<lastEventDate,1,'last');
    MR(j,2) = mean(EstimationArray(first:second,3));
end


function TextMatrix=GenMatris(MeanCAR, SignCAR,EventWindowDim)
TextMatrix='CAR';
for i=EventWindowDim(1):EventWindowDim(2)
    TextMatrix=strcat(TextMatrix,sprintf('%s %+1i',',',i));
end
%TextMatrix(length(TextMatrix))='';
for i=1:size(MeanCAR,1)
    %temp='';
    temp=sprintf('%+1i %s',EventWindowDim(1)+i-1,',');
    for j=1:size(MeanCAR,2)
        temp=strcat(temp,sprintf('%+1.3f',MeanCAR(i,j)*100),'
(',sprintf('%+1.3f',SignCAR(i,j)),'),');
    end
    temp(length(temp))='';
    TextMatrix(i+1,1:length(temp))=temp;
end


function [TextMatrix Stat]=Statistics(myAR, EventWindowDim, color, lineType)
CAR(:,1) = myAR(:,1);
for i=EventWindowDim(1):EventWindowDim(2)
    for j=i+1:EventWindowDim(2)
        CAR = [CAR CumAR(myAR,i,j,EventWindowDim)];
    end
end
StatAR=VarCAR(myAR);
StatCAR=VarCAR(CAR);
Stat=[StatAR StatCAR];

endIndex=0;
for i=1:EventWindowDim(2)-EventWindowDim(1)+1
    MeanCAR(i,i)=StatAR(1,i);
    SignCAR(i,i)=StatAR(3,i);
    beginIndex=endIndex+1;
    endIndex=endIndex+EventWindowDim(2)-EventWindowDim(1)-(i-1);
    MeanCAR(i,i+1:EventWindowDim(2)-
EventWindowDim(1)+1)=StatCAR(1,beginIndex:endIndex);
    SignCAR(i,i+1:EventWindowDim(2)-
EventWindowDim(1)+1)=StatCAR(3,beginIndex:endIndex);
end
TextMatrix=GenMatris(MeanCAR, SignCAR, EventWindowDim);


function [Stat]=VarCAR(CAR)
for i=2:size(CAR,2)
    Stat(1,i-1)=mean(CAR(:,i)); %mean
    Stat(2,i-1)=(CAR(:,i)-Stat(1,i-1))'*(CAR(:,i)-Stat(1,i-1))/(size(CAR,1)^2);
%variance
    Stat(3,i-1)=Stat(1,i-1)/sqrt(Stat(2,i-1)); %significance
end
```

```
function plotAR(Stat, StatPos, StatNeg, figName, EventWindowDim, dF, dFPos, dFNeg)
figure
set(gcf,'name',figName)
title('Mean abnormal return in the event window')
hold on
plot([EventWindowDim(1):1:EventWindowDim(2)], Stat(1,1:EventWindowDim(2)-
EventWindowDim(1)+1), 'k-','LineWidth',2)
plot([EventWindowDim(1):1:EventWindowDim(2)], StatPos(1,1:EventWindowDim(2)-
EventWindowDim(1)+1), 'r--','LineWidth',2)
plot([EventWindowDim(1):1:EventWindowDim(2)], StatNeg(1,1:EventWindowDim(2)-
EventWindowDim(1)+1), 'b-.','LineWidth',2)
for i=1:EventWindowDim(2)-EventWindowDim(1)+1
    if tcdf(abs(Stat(3,i)),dF)>0.975
        plot(EventWindowDim(1)+i-1, Stat(1,i),
'ko','MarkerFaceColor','k','MarkerSize',6)
    end
    if tcdf(abs(StatPos(3,i)),dFPos)>0.975
        plot(EventWindowDim(1)+i-1, StatPos(1,i),
'ko','MarkerFaceColor','r','MarkerSize',6)
    end
    if tcdf(abs(StatNeg(3,i)),dFNeg)>0.975
        plot(EventWindowDim(1)+i-1, StatNeg(1,i),
'ko','MarkerFaceColor','b','MarkerSize',6)
    end
end
set(gca,'xtick',EventWindowDim(1):EventWindowDim(2))
xlabel('t')
ylabel('AR')
legend('All', 'Positive news', 'Negative news', 'Significance', 'Location',
'SouthOutside', 'Orientation', 'horizontal')
plot([EventWindowDim(1):1:EventWindowDim(2)],[0 0 0 0 0],'k')


function [PosAR NegAR PosARPrev NegARPrev PosARFC Ne-
gARFC]=PosNegAR(myAR,Unemp,UnempForecast)
%2005 model
j=find(Unemp(:,1)==myAR(1,1));
p=0;
n=0;
for i=1:length(myAR)
    if Unemp(j+i-1,5)>=0
        p=p+1;
        PosAR(p,:)=myAR(i,:);
    else
        n=n+1;
        NegAR(n,:)=myAR(i,:);
    end
end
%Difference from previous month
j=find(Unemp(:,1)==myAR(1,1));
p=0;
n=0;
for i=1:length(myAR)
    if Unemp(j+i-1,3)<=0 %UURt=FURt-RURt => UURt=RURt - RURt-1 = -deltaRURt (del-
taRURt är det som finns i kolumn 3)
        p=p+1;
        PosARPrev(p,:)=myAR(i,:);
    else
        n=n+1;
        NegARPrev(n,:)=myAR(i,:);
    end
end
%Market expectations
f=find(Unemp(:,1)==UnempForecast(1,1));
UnempForecast(1:end,3)=UnempForecast(1:end,2)-Unemp(f:end,2);
j=find(myAR(:,1)==UnempForecast(1,1));
p=0;
n=0;
for i=1:length(UnempForecast)
    if UnempForecast(i,3)>=0
        p=p+1;
        PosARFC(p,:)=myAR(i+j-1,:);
    else
        n=n+1;
        NegARFC(n,:)=myAR(i+j-1,:);
    end
end
```

B.3 Forecast model

```
function Unemp=preddiff(Unemp, IP, Bond, StartDate, regrlength)

kuno=find(Unemp(:,1)>=StartDate,2);
for i=kuno(1):size(Unemp(:,1))-1
    Unemp(i+1,4)=forecast(Unemp, IP, Bond, Unemp(i,1), regrlength);
end
Unemp(kuno(2):end,5)=Unemp(kuno(2):end,4)-Unemp(kuno(2):end,3);


function [PredUnemp]=forecast(Unemp, IP, Bond, StartDate, regrlength)
i=find(Unemp(:,1)>=StartDate,1);
j=find(IP(:,1)>=StartDate,1);
k=find(Bond(:,1)<=StartDate,1,'last');
if i > regrlength+3
    y=Unemp(i-regrlength+1:i,3);
    X1=IP(j-regrlength+1-1:j-1,2);
    X2=IP(j-regrlength+1-2:j-2,2);
    X3=IP(j-regrlength+1-3:j-3,2);
    X4=Unemp(i-regrlength+1-1:i-1,3);
    X5=Bond(k-regrlength+1-1:k-1,4)-Bond(k-regrlength+1-2:k-2,4);   %Tbill3M
    X6=Bond(k-regrlength+1-1:k-1,3)-Bond(k-regrlength+1-1:k-1,2)-(Bond(k-
regrlength+1-2:k-2,3)-Bond(k-regrlength+1-2:k-2,2)); %Aaa-Baa
    X=[ones(size(X1)) X1 X2 X3 X4 X5 X6];
    beta=X\y;
else
    beta=0;
    sprintf('Regression exceedes data range')
end
T=[1 IP(j,2) IP(j-1,2) IP(j-2,2) Unemp(i,3) Bond(k,4)-Bond(k-1,4) Bond(k,3)-
Bond(k,2)-(Bond(k-1,3)-Bond(k-1,2))];
PredUnemp=T*beta;
```

Appendix C Statistical data

Twelve Months estimation window

Values in parenthesis are the calculated t-statistics for the corresponding CAR.

C.1 Summary of statistical significance

Market Expectations			
	All (%)	**Positive (%)**	**Negative (%)**
USA	CAR(-1,-1)=0.380 (2.735)	CAR(-1,-1)=0.454(2.663) CAR(1,2)=-0.611(-2.208)	-
GER	CAR(-2,-2)=-0.652(-2.576)	CAR(-2,-2)=-0.753(-2.527)	-
UK	CAR(-2,-2)=-0.379(-2.097)	-	CAR(-2,-1)=-0.662(-2.138) CAR(-2,0)=-0.934(-2.215)
JPN	-	CAR(-1,-1)=-0.398(-2.291)	-
FRA	-	CAR(-2,-2)=-0.866(-3.190)	-
SWE	-	CAR(-1,0)=0.756(2.106)	-

Boyd *et al.*			
	All (%)	**Positive (%)**	**Negative (%)**
USA	CAR(-2,0)=0.327(2.172) CAR(-2,1)=0.386(2.203) CAR(-1,0)=0.364(2.835) CAR(-1,1)=0.424(2.746) CAR(0,0)=0.254(2.417) CAR(0,1)=0.313(2.206)	-	CAR(-2,0)=0.697(3.309) CAR(-2,1)=0.818(3.347) CAR(-2,2)=0.625(2.339) CAR(-1,0)=0.571(3.214) CAR(-1,1)=0.692(3.297) CAR(-1,2)=0.498(2.036) CAR(0,0)=0.362(2.302) CAR(0,1)=0.483(2.457)
GER	CAR(-1,1)=0.574(2.462) CAR(0,1)=0.486(2.492) CAR(1,1)=0.270(2.124)	-	CAR(-1,1)=0.860(2.404) CAR(0,1)=0.809(2.833) CAR(0,2)=0.900(2.174) CAR(1,1)=0.413(2.446)
UK	CAR(-1,1)=0.353(2.192) CAR(0,1)=0.406(2.981) CAR(1,1)=0.256(3.043) CAR(0,2)=0.363(2.240)	-	CAR(0,1)=0.497(2.617) CAR(1,1)=0.318(2.602)

Boyd *et al*. continued			
JPN	-	-	-
FRA	CAR(0,0)=0.291(2.344) CAR(0,1)=0.369(2.122)	CAR(0,0)=0.332(2.368)	CAR(0,1)=0.595(2.225) CAR(1,1)=0.344(2.166)
SWE	CAR(-2,1)=0.724(2.646) CAR(-2,2)=0.641(2.055) CAR(-1,0)=0.427(2.318) CAR(-1,1)=0.731(3.214) CAR(-1,2)=0.648(2.298) CAR(0,0)=0.529(3.296) CAR(0,1)=0.833(3.898) CAR(0,2)=0.749(2.722) CAR(1,1)=0.304(2.368)	CAR(0,0)=0.588(2.649) CAR(0,1)=0.771(2.454)	CAR(-2,1)=0.979(2.449) CAR(-2,2)=1.117(2.409) CAR(-1,1)=0.922(2.847) CAR(-1,2)=1.061(2.546) CAR(0,0)=0.472(2.049) CAR(0,1)=0.891(3.066) CAR(0,2)=1.030(2.661) CAR(1,1)=0.419(2.254)

Previous unemployment			
	All (%)	**Positive (%)**	**Negative (%)**
USA	CAR(-2,0)=0.327(2.172) CAR(-2,1)=0.386(2.203) CAR(-1,0)=0.364(2.835) CAR(-1,1)=0.424(2.746) CAR(0,0)=0.254(2.417) CAR(0,1)=0.313(2.206)	-	CAR(-2,-1)=0.607(2.576) CAR(-2,0)=0.972(3.529) CAR(-2,1)=1.103(3.439) CAR(-2,2)=0.895(2.673) CAR(-1,-1)=0.322(2.539) CAR(-1,0)=0.687(2.859) CAR(-1,1)=0.818(3.010) CAR(-1,2)=0.610(2.076) CAR(0,1)=0.496(2.068)
GER	CAR(-1,1)=0.574(2.462) CAR(0,1)=0.486(2.492) CAR(1,1)=0.270(2.124)	-	CAR(-1,1)=0.984(2.181)
UK	CAR(-1,1)=0.353(2.192) CAR(0,1)=0.406(2.981) CAR(1,1)=0.256(3.043) CAR(0,2)=0.363(2.240)	CAR(0,1)=0.383(2.421) CAR(1,1)=0.249(2.694)	-
JPN	-	-	CAR(-2,-1)=0.672(2.469) CAR(-2,0)=0.773(2.240)
FRA	CAR(0,0)=0.291(2.344) CAR(0,1)=0.369(2.122)	CAR(0,0)=0.334(2.408)	-
SWE	CAR(-2,1)=0.724(2.646) CAR(-2,2)=0.641(2.055) CAR(-1,0)=0.427(2.318) CAR(-1,1)=0.731(3.214) CAR(-1,2)=0.648(2.298) CAR(0,0)=0.529(3.296) CAR(0,1)=0.833(3.898) CAR(0,2)=0.749(2.722) CAR(1,1)=0.304(2.368)	CAR(-1,1)=0.600(2.350) CAR(0,0)=0.482(2.713) CAR(0,1)=0.828(3.324) CAR(0,2)=0.669(2.041) CAR(1,1)=0.346(2.307)	CAR(-1,0)=0.804(2.020) CAR(-1,1)=1.016(2.215) CAR(-1,2)=1.097(1.982) CAR(-0,1)=0.843(2.066)

C.2 USA

All news using the smaller sample

CAR	-2	-1	0	1	2
-2	-0.245	0.135	0.131	-0.080	-0.298
	(-1.288)	(0.603)	(0.566)	(-0.300)	(-0.950)
-1		**0.380**	0.376	0.165	-0.053
		(2.735)	(1.675)	(0.586)	(-0.156)
0			-0.004	-0.215	-0.434
			(-0.022)	(-0.895)	(-1.373)
1				-0.211	-0.429
				(-1.420)	(-1.787)
2					-0.218
					(-1.317)

Positive news using market forecast

CAR	-2	-1	0	1	2
-2	-0.302	0.151	0.135	-0.186	-0.476
	(-1.312)	(0.571)	(0.517)	(-0.629)	(-1.394)
-1		**0.454**	0.437	0.116	-0.174
		(2.663)	(1.701)	(0.356)	(-0.450)
0			-0.016	-0.337	-0.627
			(-0.073)	(-1.256)	(-1.793)
1				-0.321	**-0.611**
				(-1.948)	**(-2.208)**
2					-0.290
					(-1.568)

Negative news using market forecast

CAR	-2	-1	0	1	2
-2	-0.049	0.079	0.116	0.286	0.315
	(-0.170)	(0.200)	(0.233)	(0.477)	(0.435)
-1		0.128	0.165	0.335	0.363
		(0.736)	(0.362)	(0.609)	(0.516)
0			0.037	0.207	0.236
			(0.096)	(0.400)	(0.346)
1				0.170	0.199
				(0.547)	(0.463)
2					0.029
					(0.080)

All news using the larger sample

CAR	-2	-1	0	1	2
-2	-0.038	0.073	**0.327**	**0.386**	0.225
	(-0.378)	(0.560)	**(2.172)**	**(2.203)**	(1.183)
-1		0.111	**0.364**	**0.424**	0.262
		(1.205)	**(2.835)**	**(2.746)**	(1.477)
0			**0.254**	**0.313**	0.152
			(2.417)	**(2.206)**	(0.896)
1				0.059	-0.102
				(0.662)	(-0.824)
2					-0.161
					(-1.945)

Positive news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	-0.212	-0.205	-0.067	-0.073	-0.201
	(-1.416)	(-1.154)	(-0.330)	(-0.307)	(-0.774)
-1		0.007	0.145	0.139	0.011
		(0.046)	(0.794)	(0.626)	(0.044)
0			0.138	0.132	0.004
			(1.016)	(0.651)	(0.019)
1				-0.006	-0.134
				(-0.043)	(-0.784)
2					-0.128
					(-1.267)

Negative news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	0.126	0.335	**0.697**	**0.818**	**0.625**
	(0.973)	(1.814)	**(3.309)**	**(3.347)**	**(2.339)**
-1		0.208	**0.571**	**0.692**	**0.498**
		(1.903)	**(3.214)**	**(3.297)**	**(2.036)**
0			**0.362**	**0.483**	0.290
			(2.302)	**(2.457)**	(1.156)
1				0.121	-0.072
				(1.053)	(-0.404)
2					-0.193
					(-1.485)

Positive news using previous unemployment

CAR	-2	-1	0	1	2
-2	-0.186	-0.173	0.029	0.056	-0.084
	(-1.623)	(-1.159)	(0.173)	(0.279)	(-0.377)
-1		0.013	0.216	0.242	0.102
		(0.111)	(1.448)	(1.313)	(0.467)
0			0.203	0.229	0.089
			(1.683)	(1.310)	(0.430)
1				0.026	-0.113
				(0.241)	(-0.751)
2					-0.140
					(-1.499)

Negative news using previous unemployment

CAR	-2	-1	0	1	2
-2	0.285	**0.607**	**0.972**	**1.103**	**0.895**
	(1.543)	**(2.576)**	**(3.529)**	**(3.439)**	**(2.673)**
-1		**0.322**	**0.687**	**0.818**	**0.610**
		(2.539)	**(2.859)**	**(3.010)**	**(2.076)**
0			0.364	**0.496**	0.287
			(1.779)	**(2.068)**	(0.986)
1				0.132	-0.077
				(0.823)	(-0.357)
2					-0.209
					(-1.242)

C.3 Germany

All news using the smaller sample

CAR	-2	-1	0	1	2
-2	**-0.652**	-0.371	-0.391	-0.347	-0.577
	(-2.576)	(-1.099)	(-1.043)	(-0.782)	(-0.930)
-1		0.281	0.261	0.305	0.075
		(1.078)	(0.782)	(0.666)	(0.116)
0			-0.020	0.024	-0.206
			(-0.084)	(0.064)	(-0.380)
1				0.044	-0.186
				(0.174)	(-0.461)
2					-0.230
					(-0.845)

Positive news using market forecast

CAR	-2	-1	0	1	2
-2	**-0.753**	-0.304	-0.256	-0.196	-0.462
	(-2.527)	(-0.721)	(-0.563)	(-0.381)	(-0.651)
-1		0.449	0.497	0.557	0.292
		(1.436)	(1.327)	(1.084)	(0.397)
0			0.048	0.108	-0.158
			(0.191)	(0.259)	(-0.263)
1				0.060	-0.206
				(0.196)	(-0.437)
2					-0.266
					(-0.857)

Negative news using market forecast

CAR	-2	-1	0	1	2
-2	-0.301	-0.602	-0.857	-0.868	-0.973
	(-0.682)	(-1.663)	(-1.581)	(-1.036)	(-0.772)
-1		-0.300	-0.555	-0.567	-0.672
		(-0.805)	(-0.822)	(-0.592)	(-0.500)
0			-0.255	-0.266	-0.372
			(-0.452)	(-0.322)	(-0.300)
1				-0.011	-0.117
				(-0.029)	(-0.154)
2					-0.105
					(-0.187)

All news using the larger sample

CAR	-2	-1	0	1	2
-2	-0.077	0.011	0.227	0.497	0.496
	(-0.592)	(0.061)	(0.989)	(1.967)	(1.549)
-1		0.088	0.304	**0.574**	0.573
		(0.661)	(1.551)	**(2.462)**	(1.878)
0			0.216	**0.486**	0.485
			(1.502)	**(2.492)**	(1.845)
1				**0.270**	0.269
				(2.124)	(1.345)
2					-0.001
					(-0.006)

Positive news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	0.013	0.139	0.165	0.283	0.184
	(0.067)	(0.593)	(0.497)	(0.855)	(0.485)
-1		0.127	0.152	0.270	0.171
		(0.706)	(0.574)	(0.932)	(0.521)
0			0.025	0.143	0.044
			(0.132)	(0.556)	(0.143)
1				0.118	0.019
				(0.623)	(0.074)
2					-0.099
					(-0.637)

Negative news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	-0.161	-0.110	0.285	0.698	0.790
	(-0.918)	(-0.427)	(0.899)	(1.852)	(1.559)
-1		0.051	0.447	**0.860**	0.951
		(0.263)	(1.560)	**(2.404)**	(1.898)
0			0.395	**0.809**	**0.900**
			(1.870)	**(2.833)**	**(2.174)**
1				**0.413**	0.505
				(2.446)	(1.669)
2					0.092
					(0.428)

Positive news using previous unemployment

CAR	-2	-1	0	1	2
-2	0.039	-0.010	0.203	0.424	0.447
	(0.263)	(-0.046)	(0.749)	(1.473)	(1.194)
-1		-0.049	0.163	0.385	0.407
		(-0.296)	(0.709)	(1.440)	(1.154)
0			0.212	0.434	0.456
			(1.266)	(1.925)	(1.494)
1				0.222	0.244
				(1.451)	(0.999)
2					0.022
					(0.144)

Negative news using previous unemployment

CAR	-2	-1	0	1	2
-2	-0.329	0.055	0.279	0.655	0.604
	(-1.312)	(0.170)	(0.651)	(1.311)	(0.991)
-1		0.384	0.609	**0.984**	0.933
		(1.790)	(1.675)	**(2.181)**	(1.589)
0			0.224	0.600	0.549
			(0.816)	(1.586)	(1.084)
1				0.375	0.324
				(1.642)	(0.929)
2					-0.051
					(-0.199)

C.4 UK

All news using the smaller sample

CAR	-2	-1	0	1	2
-2	**-0.379**	-0.329	-0.294	-0.117	-0.262
	(-2.097)	(-1.264)	(-1.013)	(-0.389)	(-0.704)
-1		0.049	0.085	0.262	0.116
		(0.291)	(0.376)	(0.966)	(0.324)
0			0.036	0.213	0.067
			(0.210)	(0.874)	(0.207)
1				0.177	0.032
				(1.115)	(0.130)
2					-0.146
					(-0.938)

Positive news using market forecast

CAR	-2	-1	0	1	2
-2	-0.408	-0.233	-0.108	-0.026	-0.147
	(-1.857)	(-0.724)	(-0.312)	(-0.073)	(-0.348)
-1		0.175	0.300	0.383	0.261
		(0.850)	(1.168)	(1.279)	(0.658)
0			0.125	0.207	0.086
			(0.645)	(0.752)	(0.235)
1				0.083	-0.039
				(0.468)	(-0.150)
2					-0.122
					(-0.690)

Negative news using market forecast

CAR	-2	-1	0	1	2
-2	-0.276	**-0.662**	**-0.934**	-0.430	-0.658
	(-1.055)	**(-2.138)**	**(-2.215)**	(-0.764)	(-0.861)
-1		-0.385	-0.657	-0.154	-0.382
		(-1.847)	(-1.642)	(-0.252)	(-0.469)
0			-0.272	0.231	0.003
			(-0.821)	(0.446)	(0.004)
1				0.503	0.275
				(1.484)	(0.463)
2					-0.228
					(-0.701)

All news using the larger sample

CAR	-2	-1	0	1	2
-2	-0.016	-0.069	0.081	0.337	0.294
	(-0.173)	(-0.506)	(0.484)	(1.777)	(1.377)
-1		-0.053	0.097	**0.353**	0.310
		(-0.567)	(0.744)	**(2.192)**	(1.641)
0			0.150	**0.406**	**0.363**
			(1.604)	**(2.981)**	**(2.240)**
1				**0.256**	0.213
				(3.043)	(1.680)
2					-0.043
					(-0.484)

Positive news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	0.027	0.019	0.139	0.329	0.262
	(0.242)	(0.119)	(0.660)	(1.341)	(1.112)
-1		-0.008	0.112	0.302	0.235
		(-0.057)	(0.622)	(1.318)	(1.057)
0			0.120	0.309	0.243
			(0.960)	(1.589)	(1.230)
1				0.190	0.123
				(1.660)	(0.825)
2					-0.066
					(-0.574)

Negative news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	-0.057	-0.152	0.026	0.345	0.324
	(-0.389)	(-0.709)	(0.102)	(1.202)	(0.924)
-1		-0.096	0.083	0.401	0.380
		(-0.737)	(0.441)	(1.772)	(1.265)
0			0.179	**0.497**	0.476
			(1.289)	**(2.617)**	(1.882)
1				**0.318**	0.297
				(2.602)	(1.476)
2					-0.021
					(-0.157)

Positive news using previous unemployment

CAR	-2	-1	0	1	2
-2	0.046	-0.051	0.083	0.333	0.303
	(0.484)	(-0.358)	(0.471)	(1.656)	(1.351)
-1		-0.096	0.037	0.287	0.257
		(-0.872)	(0.254)	(1.565)	(1.267)
0			0.134	**0.383**	0.353
			(1.203)	**(2.421)**	(1.953)
1				**0.249**	0.219
				(2.694)	(1.602)
2					-0.030
					(-0.287)

Negative news using previous unemployment

CAR	-2	-1	0	1	2
-2	-0.151	-0.109	0.076	0.346	0.275
	(-0.725)	(-0.358)	(0.207)	(0.837)	(0.584)
-1		0.041	0.226	0.497	0.426
		(0.237)	(0.865)	(1.556)	(1.049)
0			0.185	0.456	0.385
			(1.076)	(1.743)	(1.160)
1				0.271	0.200
				(1.542)	(0.737)
2					-0.071
					(-0.430)

C.5 Japan

All news using the smaller sample

CAR	-2	-1	0	1	2
-2	0.149 (0.797)	-0.026 (-0.094)	0.212 (0.612)	0.056 (0.146)	-0.305 (-0.671)
-1		-0.174 (-0.985)	0.063 (0.232)	-0.093 (-0.286)	-0.454 (-1.059)
0			0.237 (1.347)	0.082 (0.362)	-0.279 (-0.843)
1				-0.156 (-1.203)	-0.517 (-1.878)
2					-0.361 (-1.659)

Positive news using market forecast

CAR	-2	-1	0	1	2
-2	0.079 (0.390)	-0.318 (-1.082)	-0.143 (-0.386)	-0.324 (-0.773)	-0.790 (-1.547)
-1		**-0.398** **(-2.291)**	-0.222 (-0.786)	-0.403 (-1.213)	-0.869 (-1.889)
0			0.176 (0.851)	-0.006 (-0.022)	-0.472 (-1.221)
1				-0.181 (-1.228)	**-0.647** **(-2.033)**
2					-0.466 (-1.810)

Negative news using market forecast

CAR	-2	-1	0	1	2
-2	0.388 (0.890)	0.986 (1.744)	1.435 (1.909)	1.369 (1.733)	1.370 (1.688)
-1		0.597 (1.365)	1.047 (1.660)	0.981 (1.249)	0.981 (1.048)
0			0.450 (1.414)	0.384 (0.795)	0.384 (0.649)
1				-0.066 (-0.249)	-0.065 (-0.126)
2					0.001 (0.002)

All news using the larger sample

CAR	-2	-1	0	1	2
-2	0.084 (0.754)	0.140 (0.825)	0.129 (0.624)	0.043 (0.187)	-0.078 (-0.304)
-1		0.056 (0.490)	0.045 (0.274)	-0.041 (-0.210)	-0.162 (-0.700)
0			-0.011 (-0.105)	-0.097 (-0.650)	-0.218 (-1.153)
1				-0.086 (-0.898)	-0.207 (-1.362)
2					-0.121 (-1.099)

Positive news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	-0.072 (-0.472)	-0.110 (-0.450)	-0.115 (-0.393)	-0.224 (-0.634)	-0.356 (-0.897)
-1		-0.038 (-0.238)	-0.043 (-0.180)	-0.152 (-0.522)	-0.284 (-0.818)
0			-0.005 (-0.032)	-0.114 (-0.519)	-0.246 (-0.863)
1				-0.109 (-0.790)	-0.241 (-1.156)
2					-0.132 (-0.825)

Negative news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	0.231 (1.435)	0.376 (1.608)	0.359 (1.234)	0.294 (0.997)	0.184 (0.572)
-1		0.145 (0.890)	0.128 (0.567)	0.063 (0.237)	-0.047 (-0.153)
0			-0.017 (-0.118)	-0.082 (-0.400)	-0.192 (-0.765)
1				-0.065 (-0.486)	-0.175 (-0.795)
2					-0.110 (-0.729)

Positive news using previous unemployment

CAR	-2	-1	0	1	2
-2	-0.010	-0.104	-0.167	-0.269	-0.288
	(-0.073)	(-0.498)	(-0.664)	(-0.947)	(-0.902)
-1		-0.094	-0.157	-0.259	-0.278
		(-0.728)	(-0.789)	(-1.101)	(-1.002)
0			-0.063	-0.164	-0.183
			(-0.482)	(-0.892)	(-0.790)
1				-0.101	-0.121
				(-0.840)	(-0.688)
2					-0.019
					(-0.150)

Negative news using previous unemployment

CAR	-2	-1	0	1	2
-2	0.289	**0.672**	**0.773**	0.719	0.379
	(1.548)	**(2.469)**	**(2.240)**	(1.943)	(0.924)
-1		0.383	0.484	0.430	0.089
		(1.741)	(1.735)	(1.237)	(0.214)
0			0.101	0.047	-0.293
			(0.583)	(0.185)	(-0.903)
1				-0.054	-0.395
				(-0.345)	(-1.345)
2					-0.341
					(-1.645)

C.6 France

All news using the smaller sample

CAR	-2	-1	0	1	2
-2	-0.769	-0.589	-0.545	-0.599	-0.770
	(-3.374)	(-1.879)	(-1.623)	(-1.560)	(-1.571)
-1		0.180	0.224	0.170	-0.001
		(0.822)	(0.797)	(0.469)	(-0.003)
0			0.044	-0.010	-0.181
			(0.213)	(-0.030)	(-0.418)
1				-0.054	-0.226
				(-0.256)	(-0.758)
2					-0.172
					(-0.886)

Positive news using market forecast

CAR	-2	-1	0	1	2
-2	**-0.866**	-0.574	-0.420	-0.543	-0.805
	(-3.190)	(-1.477)	(-1.043)	(-1.205)	(-1.447)
-1		0.292	0.446	0.323	0.061
		(1.125)	(1.420)	(0.781)	(0.112)
0			0.154	0.031	-0.231
			(0.647)	(0.081)	(-0.463)
1				-0.123	-0.386
				(-0.479)	(-1.125)
2					-0.262
					(-1.208)

Negative news using market forecast

CAR	-2	-1	0	1	2
-2	-0.433	-0.640	-0.976	-0.790	-0.649
	(-1.168)	(-1.679)	(-1.852)	(-1.124)	(-0.627)
-1		-0.207	-0.543	-0.357	-0.216
		(-0.573)	(-0.957)	(-0.484)	(-0.204)
0			-0.336	-0.150	-0.009
			(-0.847)	(-0.251)	(-0.010)
1				0.186	0.327
				(0.668)	(0.577)
2					0.141
					(0.340)

All news using the larger sample

CAR	-2	-1	0	1	2
-2	-0.095	-0.089	0.202	0.280	0.193
	(-0.713)	(-0.486)	(0.900)	(1.132)	(0.679)
-1		0.006	0.297	0.375	0.289
		(0.051)	(1.677)	(1.770)	(1.125)
0			**0.291**	**0.369**	0.282
			(2.344)	**(2.122)**	(1.255)
1				0.078	-0.008
				(0.708)	(-0.052)
2					-0.087
					(-0.807)

Positive news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	0.044 (0.231)	0.049 (0.180)	0.381 (1.271)	0.177 (0.545)	0.033 (0.096)
-1		0.005 (0.026)	0.337 (1.600)	0.133 (0.508)	-0.011 (-0.036)
0			**0.332** **(2.368)**	0.128 (0.598)	-0.015 (-0.056)
1				-0.204 (-1.403)	-0.348 (-1.719)
2					-0.144 (-0.992)

Negative news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	-0.226 (-1.208)	-0.219 (-0.883)	0.033 (0.100)	0.377 (1.018)	0.344 (0.771)
-1		0.008 (0.046)	0.259 (0.924)	0.603 (1.846)	0.570 (1.381)
0			0.252 (1.251)	**0.595** **(2.225)**	0.562 (1.608)
1				**0.344** **(2.166)**	0.311 (1.317)
2					-0.033 (-0.209)

Positive news using previous unemployment

CAR	-2	-1	0	1	2
-2	-0.010 (-0.068)	-0.060 (-0.273)	0.274 (1.077)	0.316 (1.139)	0.249 (0.770)
-1		-0.049 (-0.318)	0.284 (1.419)	0.326 (1.331)	0.259 (0.880)
0			**0.334** **(2.408)**	0.376 (1.895)	0.309 (1.179)
1				0.042 (0.335)	-0.025 (-0.136)
2					-0.067 (-0.528)

Negative news using previous unemployment

CAR	-2	-1	0	1	2
-2	-0.280 (-1.038)	-0.153 (-0.456)	0.044 (0.099)	0.201 (0.401)	0.072 (0.128)
-1		0.128 (0.603)	0.325 (0.914)	0.482 (1.174)	0.353 (0.701)
0			0.197 (0.781)	0.354 (1.028)	0.225 (0.522)
1				0.157 (0.715)	0.028 (0.092)
2					-0.129 (-0.647)

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All news using the smaller sample

CAR	-2	-1	0	1	2
-2	-0.338 (-1.492)	-0.183 (-0.588)	0.224 (0.649)	0.320 (0.797)	0.313 (0.582)
-1		0.155 (0.701)	0.563 (1.890)	0.658 (1.818)	0.651 (1.235)
0			0.407 (1.567)	0.503 (1.379)	0.495 (0.933)
1				0.095 (0.438)	0.088 (0.239)
2					-0.007 (-0.027)

Positive news using market forecast

CAR	-2	-1	0	1	2
-2	-0.368 (-1.534)	-0.168 (-0.466)	0.388 (0.947)	0.448 (0.978)	0.325 (0.517)
-1		0.199 (0.723)	**0.756** **(2.106)**	0.816 (1.887)	0.693 (1.085)
0			0.557 (1.753)	0.617 (1.405)	0.493 (0.758)
1				0.060 (0.234)	-0.064 (-0.145)
2					-0.123 (-0.391)

Negative news using market forecast

CAR	-2	-1	0	1	2
-2	-0.236	-0.233	-0.341	-0.124	0.270
	(-0.410)	(-0.389)	(-0.594)	(-0.153)	(0.268)
-1		0.004	-0.105	0.112	0.507
		(0.015)	(-0.256)	(0.195)	(0.631)
0			-0.109	0.108	0.503
			(-0.336)	(0.192)	(0.680)
1				0.217	0.612
				(0.557)	(0.987)
2					0.394
					(0.934)

All news using the larger sample

CAR	-2	-1	0	1	2
-2	-0.007	-0.108	0.420	**0.724**	**0.641**
	(-0.053)	(-0.550)	(1.796)	**(2.646)**	**(2.055)**
-1		-0.101	**0.427**	**0.731**	**0.648**
		(-0.771)	**(2.318)**	**(3.214)**	**(2.298)**
0			**0.529**	**0.833**	**0.749**
			(3.296)	**(3.898)**	**(2.722)**
1				**0.304**	0.221
				(2.368)	(1.129)
2					-0.083
					(-0.630)

Positive news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	-0.075	-0.317	0.272	0.454	0.134
	(-0.432)	(-1.247)	(0.970)	(1.229)	(0.333)
-1		-0.242	0.347	0.529	0.210
		(-1.339)	(1.572)	(1.667)	(0.567)
0			**0.588**	**0.771**	0.451
			(2.649)	**(2.454)**	(1.162)
1				0.182	-0.137
				(1.039)	(-0.526)
2					-0.319
					(-1.825)

Negative news using the model of Boyd *et al.*

CAR	-2	-1	0	1	2
-2	0.057	0.088	0.560	**0.979**	**1.117**
	(0.278)	(0.296)	(1.517)	**(2.449)**	**(2.409)**
-1		0.031	0.503	**0.922**	**1.061**
		(0.165)	(1.728)	**(2.847)**	**(2.546)**
0			**0.472**	**0.891**	**1.030**
			(2.049)	**(3.066)**	**(2.661)**
1				**0.419**	0.557
				(2.254)	(1.965)
2					0.139
					(0.719)

Positive news using previous unemployment

CAR	-2	-1	0	1	2
-2	-0.021	-0.249	0.233	0.579	0.420
	(-0.148)	(-1.111)	(0.958)	(1.963)	(1.206)
-1		-0.227	0.254	**0.600**	0.442
		(-1.425)	(1.306)	**(2.350)**	(1.374)
0			**0.482**	**0.828**	**0.669**
			(2.713)	**(3.324)**	**(2.041)**
1				**0.346**	0.188
				(2.307)	(0.778)
2					-0.159
					(-1.013)

Negative news using previous unemployment

CAR	-2	-1	0	1	2
-2	0.024	0.197	0.827	1.040	1.120
	(0.081)	(0.508)	(1.602)	(1.783)	(1.775)
-1		0.173	**0.804**	**1.016**	**1.097**
		(0.772)	**(2.020)**	**(2.215)**	**(1.982)**
0			0.631	**0.843**	0.923
			(1.903)	**(2.066)**	(1.830)
1				0.212	0.293
				(0.872)	(0.880)
2					0.081
					(0.332)

Appendix D Abbreviations

AR	Abnormal Return
ASCII	American Standard Code for Information Interchange
BLS	Bureau of Labor Statistics
BM	Brownian Motion
CAR	(mean) Cumulative Abnormal Return
EMH	Efficient Market Hypothesis
IPGR	Industrial Production Growth Rate
NBER	National Bureau of Economic Research
OLS	Ordinary Least Squares