Stock Price Responses to Unemployment News: State Dependence and the Effect of Cyclicality*

Georg Bestelmeyer
Dieter Hess †

January 2010

Abstract

We study the stock market's reaction to macroeconomic news considering a firm's cyclicality, i.e., its exposure of sales to the business cycle. While theory suggests that news about overall economic conditions strongly affect stock prices, empirical evidence on the index level is mixed. Moreover, the reaction seems to be business cycle-dependent. In contrast to previous studies, we provide a more rigorous test of the state-dependence hypothesis: more cyclical firms must react stronger and more asymmetric in different phases of the business cycle. As a result, we document strong empirical evidence in favor of this cyclicality dependence, even when controlling for other potentially important factors such as book-to-market and market capitalization.

Keywords: asset pricing, information processing, macroeconomic news

JEL classification: E44, G14

* For valuable comments we are grateful to the participants of the Conference in Macroeconomic Analysis and International Finance 2010, the Eastern Finance Association Annual Meeting 2010, especially Ran Lu, the Midwest Finance Association Annual Meeting 2010, the 23rd European Conference on OR and seminar participants at the University of Cologne and the University of Konstanz.

† University of Cologne, Corporate Finance Seminar, Albertus-Magnus Platz, D-50923 Cologne, Germany, bestelmeyer@wiso.uni-koeln.de and hess@wiso.uni-koeln.de.

I. Introduction

Theory suggests that non-anticipated information about overall economic conditions strongly affects stock prices. While there is a well documented effect of monetary news, the evidence of an impact of real macroeconomic news, especially unemployment rates, is mixed. Only when conditioning on the phase of the business cycle, previous studies were able to detect a (weak) impact of unemployment news on stock markets. Shifting the focus from the index level to the firm level, we provide a more compelling test of the state-dependence hypothesis. In particular, we argue that the state-dependence hypothesis implies that the exposure of a company to the business cycle determines how strongly its stock price reacts to news about overall economic conditions. Our main hypothesis therefore states that companies with sales revenues being more sensitive to overall economic conditions, i.e. more cyclical firms, must experience stronger stock price reactions to unemployment news. To the best of our knowledge, we are the first to use firm level data to analyze the state-dependent impact of macroeconomic news. Based on a 40-year sample of individual S&P 500 companies, we find strong empirical evidence in favor of the hypothesis that stock price reactions are state-dependent. Moreover, we document a strong link between cyclicality and state-dependence. These results proof to be remarkably robust when using alternative test designs. In particular, the result does not change when using alternative business cycle measures, different concepts of measuring cyclicality and when controlling for the usual risk factors such as book-to-market and size.

The literature examining the relation between daily stock returns and macroeconomic factors can be divided into two strands according to the type of economic news investigated. One strand deals with monetary macroeconomic news such as inflation or interest rates. It clearly documents that this news influences stock markets (as well as bond markets) through the discount rate channel.[1] In contrast, the second strand, analyzing real activity news such as unemployment rates, produces mixed results. Studies focusing on bond prices clearly support a significant influence of the employment report (e.g., Hardouvelis 1987, Cook and Korn 1991, Prag 1994 and Fleming and Remolona 1997). In contrast, studies analyzing stock markets find at best a week influence. Stock market analyses face the problem that the impact on growth expectations may dilute the effect on discount rates. This is probably the reason why earlier studies – neglecting the state of the economy – find no significant impact of unemployment rate news on aggregate stock markets (e.g., Pearce and Roley 1985 and Hardouvelis 1987).[2] More recently, McQueen and Roley (1993), Boyd, Hu and Jagannathan (2005) and Andersen, Bollerslev, Diebold and Vega (2007) provide some indication of a state dependent reaction of stock markets to macroeconomic news. According to Boyd, Hu and Jagannathan (2005), unemployment news affect stock prices differently in expansions and contractions since the value of the information contained in unemployment news changes over the business cycle. They rationalize that news about growth potential and discount rate may be differently valued depending on the state of the economy. In particular, unemployment news affects stock market participants' perceptions regarding future corporate earnings or cash flows and risk-adjusted discount rates. While at times of low economic activity, information about future corporate dividends dominates, the relative importance of information about interest rates dominates during expansions.[3] This causes the seemingly odd pattern that unemployment news, i.e. the discrepancy between the expected and actual unemployment rate, have an asymmetric effect on stock prices. During recessions the

[1] For example the results of Schwert (1981), Ederington and Lee (1993) and Adams, McQueen and Wood (2004) suggest that unexpected changes in CPI, PPI and money supply (M1) have strong negative influence on stock markets by using the discount rate channel. Evidence for the impact of the Federal funds target rate is delivered by Bernanke and Kuttner (2005).

[2] The employment report is widely recognized to have the strongest market impact since it is among the first releases to be announced, and thus has the potential to move market participants expectations more than other announcements made afterwards. See e.g. Hess (2004), Chatrath, Christie-David and Moore (2006).

[3] Considering inflation surprises similar findings are made by Knif, Kolari and Pynnönen (2008). Additionally, they showed that the impact on stock markets conditions on whether investors perceive good or bad news.

dominating cash-flow information results in a positive stock market reaction, while the converse effect applies during expansions and causes stock prices to decline.

Theoretical support for such a state dependent impact of macroeconomic news comes from Blanchard (1981). He develops an IS-LM rational expectation model and shows that monetary news can be good or bad depending on the state of the economy. In the bad news case increasing interest rates induced by an unanticipated monetary expansion outweighs the effect on output growth and thus leads to a decline of the stock values. Explicitly addressing the issue of state dependence, McQueen and Roley (1993) analyze the impact of seven macro announcements, including the unemployment rate and nonfarm payrolls, on the S&P 500. Based on a business cycle definition measuring expansions and recessions as deviations from the linear trend of industrial production[4], they find that in times of a strong economy, the stock market responds negatively to news about higher real economic activity. This relationship is in line with the bad news case implied in the Blanchard (1981) model. Furthermore, Veronesi (1999) argues in the framework of a dynamic rational expectations equilibrium model that the observed effect comes from increased uncertainty. Puzzling news thus increases market participant's uncertainty about the current state of the economy and thereby affects the required risk premium. Using the alternative business cycle classification schemes of XRIC and NBER, Boyd, Hu and Jagannathan (2005) and Boyd, Jagannathan and Liu (2006) provide additional evidence of an asymmetric stock market's response to unemployment news.[5] Interestingly, the results of Poitras (2004) contradict the state dependence hypothesis. Updating the data from McQueen and Roley (1993) and establishing several robustness checks for coefficient stability as well as alternative business cycle definitions, he cannot find a state dependent reaction.

---

[4] Similar findings are made by Orphanides (1992). The response of the stock market to news about the unemployment rate is not constant and is found to vary systematically with the state of the economy.

[5] Considering inflation surprises similar findings are made by Knif, Kolari and Pynnönen (2008). Additionally, they show that the impact on stock markets conditions on whether investors perceive good or bad news.

Our study contributes to the current discussion by providing strong empirical support for the state dependence hypothesis. In particular, we document that the strength and asymmetry of the price reaction depends on firm specific determinants. Using data from the micro level, we establish a direct connection between the individual firm's reaction and unemployment news. This link among the macro- and the micro-level is cyclicality. We hypothesize, that cyclical firms, i.e. firms with a higher sensitivity to the overall economy, react stronger to news about overall economic growth. This issue of the cross-sectional behavior on real macroeconomic announcements is not explored in detail yet. A first attempt on the portfolio-level has been made by Cenesizoglu (2008). He suggests that portfolios build on size, book-to-market and industry specifications react differently to some macroeconomic news.[6] We fill this gap analyzing the differential reaction of individual stock prices to unemployment news. Note that our results suggest that the market behaves rational when cyclicality – rather than a seemingly irrational book-to-market or size effect – is found to be the key explanatory factor.

Although cyclicality is commonly regarded to be an important firm characteristic, it is quite difficult to distinguish between "cyclical" and "non-cyclical" firms. Clearly, cyclicality should be measured as growth on the micro-level relative to growth on the macro-level. However, the question is what proxies one should use. Boudoukh, Richardson and Whitelaw (1994) suggest to measure cyclicality as correlation of changes in the industrial production of a given industry with changes in the overall, i.e. economy wide, industrial production.[7] Based on this cyclicality measure, they find that the relation between industry-specific stock returns and expected inflation is strongly influenced by cyclicality.[8] Another definition comes from

[6] Analyzing returns of Fama-French portfolios sorted on size and book-to-market he finds that large and growth stocks react significantly stronger than small and value stocks while for the industry portfolios no clear-cut pattern can be found. While some industries seem to react, others don't. Overall the result for the unemployment rate is rather weak, with and without considering the business cycle.

[7] Another study by Berman and Pfleeger (1997) uses the correlation of yearly growth in industry final demand and employment with yearly growth in GDP to identify industries which are more prone to business cycle swings. However their results are quite comparable to ours.

[8] While stock returns of noncyclical industries tend to exhibit a positive covariance with expected inflation, a negative covariance is observed for cyclical industries.

Petersen and Strongin (1996) who measure cyclicality as the percentage change in real value added on industry level relative to the economy. They find the durable-goods industries to be approximately three times more cyclical than the non-durable goods industries.[9] Our definition resembles these previous approaches but differs in the way that we use a micro-level growth proxy which is directly aggregated from individual firm data and therefore provides a finer and more direct link. The classifications arising from our cyclicality definition are largely in line with previous classification results.[10] Using this cyclicality definition we find that the news impact of the unemployment rate is far stronger for cyclical firms than for non-cyclical firms.

Our approach yields several advantages: First of all, in contrast to previous studies focusing on indices, we analyze panel data. Our dataset consists of S&P 500 firms over a period of nearly 40 years and thus provides the necessary statistical power. Secondly, using cross-sectional data enables us to analyze the effects of firm specific characteristics and therefore to uncover a strong influence of cyclicality. Thirdly and most importantly, the cyclicality hypothesis strengthens previous evidence of a state dependent stock market response to real activity news. In particular, the hypothesis rationalizes that the relative value of information bundled in real activity news can change over the business cycle. Therefore the cyclicality argument provides an explanation for the seemingly irrational behavior that bad news from the labor market is good news for the stock market when the economy is an expansion, while the reverse is true for contractions. Moreover, the cyclicality hypotheses provides the strongest possible prove for the existence of the business cycle effect and explains the heterogeneous reaction of firms in the cross-section.

[9] The focus of their paper is to find determinants for cyclicality. Therefore, they emphasize the cost structure (proportion of variable and quasi-fixed costs), market concentration and labor hoarding effects as possible reasons for cyclicality. In this context, Sharpe (1994) finds low levered firms to be more prone to labor hoarding.

[10] For example, we find firms from the Metal, Paper or Rubber and Plastic Products industry to be far more cyclical than firms from the Food, Healthcare and Tobacco industries.

The remainder of the paper is organized as follows. Section II describes the dataset, the method for forecasting the surprises in the unemployment rate and our cyclicality definition in more detail. Section III presents the empirical results on the asymmetric behavior of returns considering state dependence and cyclicality. We then discuss alternative explanations and the robustness of the results in Section IV. Concluding remarks and directions for further research are provided in Section V.

II. Data Description

Our sample covers the period May 1967 to December 2007. Daily returns ex dividends, prices and shares outstanding for S&P 500 index constituents are retrieved from the CRSP US daily stocks and index file. Additionally, accounting data, such as sales or book value of equity, are obtained from the COMPUSTAT quarterly fundamentals file. In order to measure differential stock price reactions over the business cycle we include only firms which lived at least for one full cycle. Specifically, we exclude firms which have no record for at least six recession and 18 expansion months. Our research design assumes an efficient market, i.e. an immediate price adjustment to new information. Therefore, we keep only days when the employment report could have an impact on prices for the first time. We retain 204.898 observations with each observation representing one firm on one announcement day.

A. Measuring Cyclicality

To identify cyclical firms, we use, analogue to Boudoukh, Richardson and Whitelaw (1994), the correlation of output growth on the micro and macro level, i.e. we correlate sales on the industry level with overall industrial production (IP). We define firms as cyclical if the correlation is above the median. If we assume that cyclical firms react stronger, using the median tends to dilute the supposed cyclicality effect.[11] The sales figure as proxy for growth on the micro side provides some valuable advantages: Firstly, sales directly react to a decrease in demand during an economic downturn. Secondly, the sales figure is most robust against managerial discretion arising from accounting options and/or extraordinary events. Moreover, opposite to profit measures like EBIT or net income, sales figures do not incorporate cost structure and tax effects which potentially mute the supposed cyclicality. To compare apples with apples we choose the IP index to measure the output attributable to US firms on a macro-level. IP covers nearly everything that is physically produced or mined in the US. Additionally, IP is known to react fairly quickly to up and down swings of the business cycle.

When calculating the correlation we have to regard some possible pitfalls. First of all, M&A activities may lead to spurious correlations, if computed on the firm level, when sales rise due to an acquisition although the economy actually is in a recession. Therefore, we aggregate sales on an industry level.[12] Calculating the correlation of aggregated industry sales with IP deletes this effect as long as it is an intra-industry merger. Intuitively a more coarse meshed industry definition will reduce the bias arising from inter-industry mergers. A second technique to temper the merger effect is the procedure used for the industry sales growth rate calculation. To assure not to overestimate sales growth when new firms enter the economy or to underestimate it, if old firms die from the panel, we use sales only from firms for which records are observable in both periods. Additionally, we exclude observations which are marked as non-comparable because of M&A activities.[13] Although our focus is on the S&P 500 firms, we include all firms available at the COMPUSTAT tapes when calculating industry sales. This assures that we capture the complete market volume of an industry and therefore avoid the problem arising when industry sales consist of only a handful firms or if

[11] For example, we would expect a much stronger cyclicality effect when using the top 30% quartile as cutting edge for cyclicality.
[12] We excluded observations with an unreasonable negative sales figure when aggregating the sales on index level.
[13] COMPUSTAT provides an item for the “Comparability Status”. When calculating the industry-sales, we neglected observations marked as non-comparable due to M&A activities.

changes in the composition of the S&P 500 index occur. Our results show that these procedures substantially temper the merger effect. Moreover, when calculating IP growth we use unrevised data to assure that we only use information available for market participants at that particular point in time. Finally, we use year-over-year growth rates from both the IP and the industry sales to exclude seasonal patterns.

As discussed above, we use different industry aggregation levels: First, we differentiate industries according to the standard industry classification scheme (SIC-codes), using different levels, i.e. the fine sort of the 4-digit industry level as well as Industry Groups (3-digit SIC-level), Major Groups (2-digit SIC-level) and Industry Divisions (1-digit SIC-level).[14] Second, to facilitate a comparison to Cenesizoglu (2008) and Beber and Brandt (2008), we also use the Fama-French 48 (FF48) industry portfolio scheme.[15] The correlations for the S&P 500 firms with respect to different industry definitions are shown in Table 1.

[Insert Table 1 here]

The comparison of the correlation distribution yields some interesting insights. A more dense distribution of correlations is observed for the coarser industry classification, i.e. less outliers occur, whereas for the SIC 4-digit industry classification an unreasonably high negative correlation of -0.38 is observed at the minimum. This would mean that sales in this industry decrease on average while the economy is in an expansion.[16] Aggregating on the SIC Major Group level mitigates this because the average number of firms per industry increases when the number of industries is reduced. On the other hand a very coarse meshed industry definition like the SIC Division structure would neglect the heterogeneity across the

[14] The 4-digit SIC codes are assigned by the United States Department of Labor, Occupational Safety & Health Administration (OSHA) depending on the operating business of the firm. For further readings about the SIC structure please refer to http://www.osha.gov/oshstats/index.html.

[15] The FF48 industry portfolios are constructed by assigning the SIC classified industries to 48 portfolios. For further information concerning the Fama-French industry portfolios please refer to the website of Kenneth French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html).

[16] An economic explanation might be that of substitutable goods. If the economy is in a recession the demand of butter, for example, will temporary shift to margarine which leads to rising sales in this industry and thus a negative correlation. Nevertheless looking at the 10% percentile the correlations are very close to zero indicating a non-cyclical demand and showing that this is a very limited phenomenon.

industries. A reasonable trade-off seems to focus on the SIC 2-digit Major Group definition. We think this balances problems arising from M&A activities, an insufficient number of firms and the industry shades. However, we show in section IV that our results are insensitive to the use of alternative industry and thus alternative cyclicality definitions.

B. Unemployment Rate Announcements

There are dozens of macroeconomic reports released either by the federal government or private groups on a weekly, monthly or quarterly basis. We focus on the monthly unemployment rate (UN) published by the Bureau of Labor Statistics (BLS), since this figure is viewed as the most influential announcement and it is frequently cited to move the markets. The reason is that the unemployment rate is the first monthly indicator issued from statistical agencies providing evidence on the economy as a whole.[17] The announcements are usually made at 8:30 a.m. on the first Friday of a month. Nevertheless, some announcements were made on other days. Accounting for this, we use the original announcement day. Moreover, in some cases the employment report was published on non-trading days, i.e. days on which the stock market was closed. In this case we use the first trading day after the announcement.[18]

Since the focus of this paper is to analyze how news about overall macroeconomic growth embedded in the unemployment rate influence stock markets, it is crucial to identify the news component, i.e. the unanticipated part of the information. Following Boyd, Hu and Jagannathan (2005) we use a forecast model for the unemployment rate and then calculate the surprise component as the difference between the actual and the forecasted unemployment rate. In particular, we follow "Method 3" as described in Boyd, Hu and Jagannathan (2005)

[17] The unemployment rate reflects the percentage of the civilian workforce that is unemployed and is regularly collected from a survey of households.

[18] For example at April 1st 1988 the BLS released the employment report while exchanges were closed due to Goods Friday. We then used April 4th 1988 as the first trading day after the announcement when the UN information was incorporated into prices. In the following we also use the term announcement days for these.

and employ it on our longer time period from May 1967 to December 2007.[19] However, we deviate in one important aspect from the procedure suggested by BHJ. Since the input data for the forecasting model gets regularly revised, an important point is to assure equal information sets. For that we conduct the estimation in two ways. The first estimation directly follows BHJ in the use of final release data but employs only data available up to one year before the estimation date. This estimation differs only in the employed time period from BHJ and will be referred to as "BHJ^{long}". Additionally, the second estimation method ("HB") employs unrevised data only.[20] This is an important point since only information available to market participants at that particular point in time is used. This should match market participants information sets best.

As a reference, we employ also the original surprises used in Boyd, Hu and Jagannathan (2005) and Boyd, Jagannathan and Liu (2006) for the time period from June 1972 to December 2004, labeled as "BHJ". They were kindly provided by the authors.[21] Finally, we employ surprises measured against analyst forecast survey by the Money Market Services (MMS).[22;23] These are labeled as "MMS". Unfortunately the MMS survey data is limited to the time period from January 1980 to November 2007. [24] Interestingly, our surprises have the highest correlation with "MMS". This suggests that our forecasts are a reasonable

[19] A detailed description of the forecasting model could be found in Boyd, Hu and Jagannathan (2005). The model employs the change in the unemployment rate, some lags of the growth in industrial production as well as the change in the 3-month T-bill rate and the default yield spread between Baa and Aaa corporate bonds. However, they focus on a shorter time period from June 1972 to December 2000.

[20] Data series are obtained from the ALFRED® database of the St. Louis Fed http://alfred.stlouisfed.org .

[21] We especially thank Ravi Jagannathan, John Boyd and Qianqui Liu for providing us with their data.

[22] MMS is the most widely used data provider in studies of macroeconomic announcements, since it was the first to collect consensus estimates. Studies which use MMS forecasts include, among others, Hardouvelis (1988), McQueen and Roley (1993), Balduzzi, Elton and Green (2001), Flannery and Protopapadakis (2002), Chatrath, Christie-David and Moore (2006) and Hautsch and Hess (2007).

[23] MMS conducts a survey every Friday, asking academicians and practitioners to forecast macroeconomic figures which will be released during the following week. It includes the median consensus forecast for the unemployment rate from which we then calculate the surprise, using the unrevised unemployment data.

[24] The performance of these forecasts has been scrutinized, for example, by Pearce and Roley (1985), McQueen and Roley (1993), Almeida, Goodhart and Payne (1998), Moersch (2001) and Schirm (2003). These studies provide evidence that forecasts collected by MMS are either unbiased or exhibit only a very small bias. Moreover, MMS forecasts are found to be more accurate than time series models.

approximation of market participants' expectations while being available for a much longer period.

However what is most important for the analysis is that none of our results are particularly sensitive to the choice of the news component. We will show that later on in the robustness section and conduct the analysis in section III with surprises from the forecast based on unrevised data.

C. Daily Returns on Stocks

We use the returns excluding dividends of firms listed in the S&P 500 obtained from the CRSP daily stocks file. Panel A of Table 2 reports average daily returns on announcement and non-announcement days. Additionally Panel B shows average returns on announcement days for different states of the economy according to the CFNAI classification.

[Insert Table 2 here]

Mean returns for S&P 500 firms are somewhat higher on announcement days then on non-announcement days. On the announcement days stock returns during expansions are substantially higher than during recessions. During recessions stock returns are negative on average. If we partition the returns for cyclical and non-cyclical firms (Panel C), we find that on average the return for cyclical firms is about 53% higher. This is due to higher returns of cyclical firms during expansions and also during recessions (see Table 3).

[Insert Table 3 here]

Cyclical firms have on average 34% higher returns during an expansion. Surprisingly, they have also a higher return in recessions. Distinguishing between the news types, i.e. whether employment news are good or bad, we also find an asymmetric reaction. While the response of cyclical firms on "good news" is negative on average and comparable to the return of non-cyclical firms, it is about 41% higher on "bad news". Thus the economy is usually in an expansion, cyclical firms are more prone to business cycle swings because they react stronger on news about the overall economy.

D. Business Cycle Indicator

To investigate the effect of macroeconomic news dependent on the state of the economy, we need an appropriate measure to classify periods of expansions and recessions. For our analysis we use three different classification schemes to analyze the robustness of the results. These are the National Bureau of Economic Research (NBER) turning points, the experimental coincident recession index (XRIC) and the Chicago Fed National Activity Index (CFNAI). In earlier studies, NBER-turning points have frequently been used. They are easy obtainable but have the drawback, that they are not available in real-time, i.e. they incorporate information not available to market participants at an announcement day, and therefore, are presumably not well suited to measure market participants' assessment of the business cycle. Our second business cycle indicator is the XRIC constructed by Stock and Watson (1989) which measures the probability of a current recession. Boyd, Hu and Jagannathan (2005) point out that the XRIC is preferable over the NBER as an indicator for the business cycle. This is because it uses only information that is publicly known at a particular point in time, what makes it a better measure than the ex post procedure applied by the NBER Business Cycle Dating Committee. Unfortunately, XRIC data are only available until December 2003, which restricts our sample period.[25] We follow Basistha and Kurov (2008) and Hess and Kreutzmann (2009) and use the most direct successor which is the CFNAI.[26] The CFNAI is the first principal component of 85 monthly indicators of national economic activity. Its construction follows

[25] However the XRIC retired and calculation ended in December 2003. Historical values are obtained from the website of James Stock and Mark Watson (http://ksghome.harvard.edu/~JStock/xri/).
[26] Historical values of the CFNAI are obtained from the Website of the Chicago Fed (www.chicagofed.org).

the methodology in Stock and Watson (1999).[27] According to the Chicago Fed, a drop of the 3-month moving average of the CFNAI below -0.7 indicates an increasing probability that a recession has begun. An increase of the 3-month moving average of the CFNAI above 0.2 indicates a significant probability that a recession has ended. Applying this rule, we recode the CFNAI and use its binary form. Following the CFNAI scheme, our sample period spans seven business cycles with a total of 126 recession and 362 expansion months. Table 4 gives a detailed picture and compares the three different business cycle indicators.[28]

[Insert Table 4 here]

Therefore the US economy is in expansion at the beginning of the sample period and switches to a one year recession in January 1970. The subsequent expansion was interrupted by a one year recession from July 1974 to June 1975 and ended in February 1980. The following two recessions at the beginning of the 1980's and the one at the beginning of the 1990's lasted in total 67 months until December 1992. The last relevant recession in our sample covers the time period from January 2001 through October 2003. The current recession is of minor importance since it starts in December 2007, the last month of our sample period. Comparing NBER and CFNAI schemes, it is striking that CFNAI has almost twice as much recession months and average duration of a recession which is about 64% higher. However, most of this difference is due to the 1989 – 1992 and the 2001 – 2003 periods where the CFNAI suggests that the economy was for 42 respectively 34 months in recession while NBER indicates 8 recession months.

For the following analysis of our cyclicality hypotheses presented in section III we use the CFNAI as business cycle indicator. However we show in section IV that our results remain virtually unchanged when different business cycle measures are employed.

[27] The index is constructed to have an average value of zero and a standard deviation of one. A positive index corresponds to growth above trend and a negative index corresponds to growth below trend.
[28] For a better comparability we also recoded the XRIC according to the CFNAI rules.

III. Asymmetries in the reaction of cyclical and non-cyclical firms

As a starting point, we investigate whether the response of the stock markets return to unemployment news arrival is state dependent. Applying an event-study approach, we analyze the daily stock returns of S&P 500 firms according to equation (1).[29]

$$ret_{i,t} = \alpha + \beta_1 \cdot D_t^{rec} \cdot S_t^{UN} + \beta_2 \cdot \left(1 - D_t^{rec}\right) \cdot S_t^{UN} + \beta_3 \cdot BtM_{i,t} + \beta_4 \cdot MC_{i,t} + u_t \qquad (1)$$

$ret_{i,t}$ denotes the return of firm i on announcement day t ignoring dividends. S_t^{UN} denotes the surprise component in the unemployment rate announcement. D_t^{rec} is a variable indicating the state of the economy. As discussed in the previous section, we use the CFNAI. Therefore, D_t^{rec} equals one if the economy is in a recession on announcement day t and zero otherwise. $MC_{i,t}$ ($BtM_{i,t}$) denotes the market capitalization (book-to-market value) of firm i on announcement day t. We include them to control for different levels in this ratios and thus to account for the results of Cenesizoglu (2008). However, to facilitate a comparison to previous studies, we estimate equation (1) and later on equation (2) with and without the control variables (labeled as "I" and "II" respectively). β_1 measures the stock price sensitivity to unexpected unemployment news during contractions and β_2 during expansions.[30] We expect a negative β_1 and a positive β_2 coefficient. This implies that positive news from the labor market, i.e. a lower than expected unemployment rate, has on average a positive stock market effect during contractions and a negative effect during expansions. As pointed out by Boyd, Hu and Jagannathan (2005) this is due to the competing impact of unemployment news through the discount rate and the growth expectations channel. In contractions the effect on growth expectations dominates while it is converse during an expansion. Whereas previous empirical evidence on the index level is rather weak, estimating equation (1) on the individual

[29] Boyd, Hu and Jagannathan (2005) use a similar approach to analyze news impact on the index-level.

[30] To avoid problems of heteroscedasticity all regressions are estimated with robust standard errors that account for clustering at the company level. Note that clustered standard errors per construction control for heteroscedasticity (Petersen 2009).

firm level and on an extended sample period should provide stronger results given the state dependence hypothesis holds. For further reference we label equation (1) “restricted” since it does not account for cyclicality. The results are given in Table 5.

[Insert Table 5 here]

As expected the sign of β_1 (β_2) is negative (positive) and both coefficients are highly significant, i.e. on the 1% level. Therefore, good news from the labor market during a boom period is bad news for stocks, while it is good news during a recession. Economically, this might signal an overheating economy, leading to relatively higher discount rates and thus decreasing prices. Remarkably, the inclusion of the control variables does not change the significance levels and impacts only very slightly on the coefficients. However, the results from our analysis on the firm-level strongly support the state dependence hypothesis. As expected the evidence is much stronger than previously obtained results for the index-level.

While the above results suggest strong asymmetries over the business cycle, a more compelling argument is provided by our main hypothesis: If the state dependence holds, i.e. that interest and growth information bundled in employment news are valued differently in different business cycle phases, then more cyclical firms should respond stronger and more asymmetrically than non-cyclical firms. This provides a much more demanding test of the state dependence hypothesis. Therefore, we extend equation (1) and introduce a variable accounting for differences in cyclicality of sales across firms:

$$
\begin{aligned}
ret_{i,t} = \alpha &+ \beta_1 \cdot D_t^{rec} \cdot S_t^{UN} + \beta_2 \cdot \left(1 - D_t^{rec}\right) \cdot S_t^{UN} \\
&+ \beta_3 \cdot D_t^{rec} \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_4 \cdot \left(1 - D_t^{rec}\right) \cdot D_i^{cyclical} \cdot S_t^{UN} \quad (2) \\
&+ \beta_5 \cdot BtM_{i,t} + \beta_6 \cdot MC_{i,t} + u_t
\end{aligned}
$$

$D_t^{cyclical}$ is a dummy variable indicating whether an individual firm is classified as cyclical, i.e. whether the corresponding correlation of output growth on the SIC 2-digit level with IP growth is larger than the median correlation in our sample. Results for alternative cyclicality definitions are quite similar (see section IV). The incremental impact of macroeconomic news on cyclical firms is captured by β_3 during recessions and β_4 during expansions. If cyclical firms react stronger, these coefficients must be significant by different from zero and have the same signs as the β_1 and β_2 coefficient.

We refer to equation (2) as "unrestricted". The results are also presented in Table 5. As hypothesized, the sign of β_3 (β_4) is negative (positive) and both coefficients are highly significant. To capture the entire effect for cyclical firms in a recession (expansion) one simply has to sum the β_1 (β_2) and β_3 (β_4) coefficients. Overall, these results strongly suggest that cyclicality drives the state dependence even after controlling for different levels in book-to-market and size. As in the "restricted" case the results with and without control variables are almost identical. Cyclical firms react much stronger than non-cyclical firms, both in expansions and in recessions. During a recession cyclical firms react about 76% stronger than non-cyclical firms (-0.507 vs. -0.288), while during an expansion cyclical firms react about 37% stronger (0.553 vs. 0.404). This is confirmed by a Likelihood-ratio test comparing the unrestricted model (with cyclicality) to the restricted version, which is nested in the unrestricted model. The LR-test strongly rejects the restricted model (i.e. on the 1% level) and thus clearly supports our main hypotheses. Cyclicality drives state dependence providing the key explanatory factor for asymmetric stock returns across different business cycle phases.

IV. Robustness

Our analysis depends on the use of three proxy variables, specifically our cyclicality definition, the recession indicator and the surprise estimates. Therefore, it is important to analyze the sensitivity of the results to alternative specifications of these measures. In particular, we re-estimate equation (2) using the previous outlined alternative methods to measure cyclicality, business cycle phases and surprise components. This analysis reveals that the results are remarkably robust.

Concerning the business cycle, we substitute the CFNAI with the NBER-turning points as well as the XRIC. This facilitates a comparison to previous studies like Poitras (2004) or Boyd, Hu and Jagannathan (2005). While these alternative measures yield some disadvantages described in section II, the results remain virtually unchanged (see Table 6).

[Insert Table 6 here]

Most remarkably, the estimated coefficients remain virtually unchanged when we employ alternative business cycle definitions. Also the statistical significance remains strong. While virtually no difference is observed between CFNAI and NBER, the results are slightly less significant for the XRIC. This may be attributable to the smaller sample period associated with it.

Another issue may be our cyclicality definition. Therefore, we use three different ways to measure cyclicality. First, we implement alternative variables to measure macroeconomic growth. Second, we change the industry aggregation level. Finally, we alter the truncation condition for differentiating between cyclical and non-cyclical firms.

In line with Boudoukh, Richardson and Whitelaw (1994), IP is used as proxy for macroeconomic growth in the above analysis. Nevertheless, other variables might be more appropriate. Therefore, we also use the growth in real gross domestic product (GDP) and the growth in durable goods orders (DGO). The GDP is of course the foremost quarterly report on overall economic growth. It is often cited to help financial planners making sales growth forecast or composing business plans. It reflects the final value of all output in the U.S. economy, regardless of whether sold or placed in inventory. Therefore, it measures a somewhat wider range than sales, but seems comparable with firm sales. The monthly DGO figure is released by the Census Bureau, Department of Commerce and is a key indicator of future manufacturing activity. It is highly sensitive to fluctuations in demand and therefore provides another interesting benchmark for firm sales. The results for the three alternative macro-growth proxies are shown in Table 7.

[Insert Table 7 here]

Irrespective of the implemented macro variable the results remain strong. Again, cyclical firms react significantly stronger to unemployment rate news than non-cyclical firms. Interestingly, for all three macro growth proxies the magnitude of the coefficients is nearly the same. However, the cyclicality definition based on GDP yields somewhat stronger results. We observe a substantially stronger impact in recessions while in expansions the estimated coefficients are approximately at the same level. With only two exceptions, all coefficients are significant at the 1% level.

Another concern might be the industry aggregation level in our cyclicality definition. As discussed in section II we face a trade-off between controlling for M&A activities and a narrow industry definition. Therefore, we analyze the robustness of the results with respect to alternative industry aggregations, namely different SIC aggregation levels based on the 4-digit code as well as the Fama-French 48 industry classifications. The results of this analysis are presented in Table 8.

[Insert Table 8 here]

Basically, Table 8 shows that the results are insensitive to the choice of different industry aggregation levels. For all measures, cyclical firms react significantly stronger to unemployment rate news than non-cyclical firms. This result is reinforced by the LR-Tests comparing the estimated model to its restricted counterparts (i.e. specifications excluding the cyclicality coefficients). For five out of five different industry aggregation levels the test rejects the restricted model on the 1% level. Moreover, the variation concerning the magnitude of the cyclical coefficients seems little at least for the SIC 2 to SIC 4 industry definition, what strengthens our hypothesis, respectively our cyclicality definition.

A further issue may be the truncation condition for discriminating between cyclical and non-cyclical firms. We report only results for the median correlation. However, we would expect the tails of the distribution to react stronger. Therefore, using the median instead of e.g. the top 25% quartile seems to be a very conservative truncation point. In fact, repeating the analysis with different truncation points reveals that the median yields the weakest results. For the sake of brevity, these results are omitted.

Last but not least, our method to measure unanticipated information may be a concern. We tried to establish a very conservative method for forecasting the UN rate by using only unrevised data, i.e. data being actually obtainable for market participants at a particular point in time. Nevertheless, we provide additional estimation results using three alternative methods to obtain surprises. Namely, surprises calculated on revised data, i.e. according to Method 3 in Boyd, Hu and Jagannathan (2005) but for our extended sample ("BHJ^{long}"), the original surprises used in this study ("BHJ"), and surprises based on the MMS survey ("MMS"). The results of this analysis are shown in Table 9.

[Insert Table 9 here]

As expected, the estimated coefficients vary to some extent across different measures of unanticipated information. Nevertheless, the results for the reaction of cyclical in the recession period are remarkably stable. In particular, we would have expected to obtain much weaker results when using MMS data since these are available only after 1980 and thus reduce our sample period substantially. Surprisingly, the results appear to be even somewhat stronger. In particular, we find a much stronger cyclicality effect in recession. The results for surprises extracted from unrevised data ("HB") versus revised data ("BHJ^{long}" and "BHJ") are quite comparable in significance. Nevertheless, estimated coefficients are somewhat smaller for surprises based on unrevised data. This indicates that the method employed here provides the most conservative results. Nevertheless, the results strongly confirm the state dependence hypothesis. Even more important, our results indicate that the state dependence is driven mainly by cyclicality. Cyclical firms react significantly stronger to unemployment rate news than non-cyclical firms.

V. Conclusion

Thus far, stock market's reaction on unemployment news has been mostly analyzed on the index level. However, little is known about the reaction of the cross section to news about real economic activity. We close this gap and analyze the differential behavior of firms to unemployment rate news. This analysis contributes to two major questions: First, we provide strong empirical evidence that unemployment news contain pricing relevant information. Moreover, we acknowledge the pattern that good news from the employment report is bad news for stock prices while the economy is in an expansion. Thus there is a substantial support in favor of the supposed state dependence hypothesis of previous studies, i.e. the asymmetric behavior of stock prices to unemployment news over the business cycle.

Second, we establish a direct link between state dependent stock price reactions and firm specific determinants. We document that a firm's exposure to overall macroeconomic conditions, i.e. its cyclicality, explains a substantial portion of the strength and asymmetry of reactions to news. Intuitively, more cyclical firms must react stronger. This is driven by a higher sales sensitivity to overall economic growth. Therefore our results clearly indicate that the asymmetric stock price reaction on firm level is at least partly due to cyclicality even when controlling for differences in book-to-market and size. While cyclicality gives the link among the macro- and the micro-level we show that firms with a higher sensitivity to the overall economy react stronger in magnitude to news concerning economic conditions.

Additionally, the cyclicality link provides the most compelling argument for the business cycle dependent stock market reaction to unemployment news.

Our results provide some potentially important insights for asset pricing factor models which are widely applied in securities pricing. Factor loadings should at least partly account for the asymmetric reaction of the stock market depending on the state of the economy. Future research may intend to disentangle the overall stock price reaction on the firm-level into responses of the expected growth rate as well as the discount rate.

References

Adams, G., McQueen, G. and Wood, R. (2004): The effects of inflation news on high frequency stock returns, Journal of Business, 77 (3), 547-574.

Almeida, A., Goodhart, C. and Payne, R. (1998): The effects of macroeconomic news on high frequency exchange rate behavior, Journal of Financial and Quantitative Analysis, 33 (3), 383-408.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Vega, C. (2007): Real-time price discovery in global stock, bond and foreign exchange markets, Journal of International Economics, 73 (2), 251-277.

Balduzzi, P., Elton, E. J. and Green, T. C. (2001): Economic news and bond prices: Evidence from the US treasury market, Journal of Financial and Quantitative Analysis, 36 (4), 523-543.

Basistha, A. and Kurov, A. (2008): Macroeconomic cycles and the stock market’s reaction to monetary policy, Journal of Banking and Finance, 32 (12), 2606-2616.

Beber, A. and Brandt, M. W. (2009): Resolving Macroeconomic Uncertainty in Stock and Bond Markets, Review of Finance, 13 (1), 1-45.

Berman, J. and Pfleeger, J. (1997): Which industries are sensitive to business cycles?, Monthly Labor Review, 120 (2), 19-25.

Bernanke, B. S. and Kuttner, K. N. (2005): What explains the stock market’s reaction to Federal Reserve Policy?, Journal of Finance, 60 (3), 1221-1257.

Blanchard, O. J. (1981): Output, the stock market and interest rates, American Economic Review, 71 (1), 132-143.

Boudoukh, J., Richardson, M. and Whitelaw, R. F. (1994): Industry Returns and the Fisher Effect, Journal of Finance, 49 (5), 1595-1615.

Boyd, J. H., Hu, J. and Jagannathan, R. (2005): The stock market's reaction to unemployment news: Why bad news is usually good for stocks, Journal of Finance, 60 (2), 649-672.

Boyd, J.H., Jagannathan, R. and Liu, Q. (2006): The Stock Market’s Reaction to Unemployment News, stock-bond return correlations, and the state of the economy, Journal of Investment Management, 4 (4), 1-18.

Cenesizoglu, T. (2008): Size, Book-to-Market Ratio and Macroeconomic News, HEC Montreal, Working Paper.

Chatrath, A., Christie-David, R. and Moore, W. T. (2006): The macroeconomic news cycle and uncertainty resolution, Journal of Business, 79 (5), 2633-2657.

Cook, T. and Korn, S. (1991): The Reaction of Interest Rates to the Employment Report: The Role of Policy Anticipations, Federal Reserve Bank of Richmond, Economic Review, 77 (5), 3-10.

Ederington, L. H. and Lee, J. H. (1993): How Markets Process Information: News Releases and Volatility, Journal of Finance, 48 (4), 1161-1191.

Flannery, M. J. and Protopapadakis, A. A. (2002): Macroeconomic factors do influence aggregate stock returns, Review of Financial Studies, 15 (2), 751-782.

Fleming, M. and Remolona, E. (1997): What moves the bond market?, Economic Policy Review, 3 (4), 31-50.

Hardouvelis, G. A. (1987): Macroeconomic Information and Stock Prices, Journal of Economics and Business, 39 (2), 131-140.

Hardouvelis, G. A. (1988): Economic news, exchange rates and interest rates, Journal of International Money and Finance, 7 (1), 23-35.

Hautsch, N. and Hess, D. (2007): Bayesian learning in financial markets: Testing for the relevance of information precision in price discovery, Journal of Financial and Quantitative Analysis, 42 (1), 189-208.

Hess, D. (2004): Determinants of the relative price impact of unanticipated information in US macroeconomic releases, Journal of Futures Markets, 24 (7), 609-629.

Hess, D. and Kreutzmann, D. (2009): Earnings Expectations and Macroeconomic Conditions, University of Cologne, Working Paper.

Knif, J., Kolari, J. and Pynnönen, S. (2008): Stock market reaction to good and bad inflation news, Journal of Financial Research, 31 (2), 141-166.

McQueen, G. and Roley, V. V. (1993): Stock prices, news, and business conditions, Review of Financial Studies, 6 (3), 683-707.

Moersch, M. (2001): Predicting Market Movers: A Closer Look at Consensus Estimates, Business Economics, 36 (2), 24-29.

Orphanides, A. (1992): When good news is bad news: Macroeconomic news and the stock market, Board of Governors of the Federal Reserve System, Working Paper.

Pearce, D. K. and Roley, V. V. (1985): Stock prices and economic news, Journal of Business, 58 (1), 49-67.

Petersen, B. and Strongin, S. (1996): Why are some industries more cyclical than others?, Journal of Business and Economic Statistics, 14 (2), 189-198.

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. Review of Financial Studies, 22 (1), 435-480.

Poitras, M. (2004): The impact of macroeconomic announcements on stock prices: In search of state dependence, Southern Economic Journal, 70 (3), 549-565.

Prag, J. (1994): The Response of Interest Rates to Unemployment Rate Announcements: Is there a natural rate of Unemployment?, Journal of Macroeconomics, 16 (1), 171-184.

Schirm, D. C. (2003): A Comparative Analysis of the Rationality of Consensus Forecasts of U.S. Economic Indicators, Journal of Business, 76 (4), 547-561.

Schwert, G. W. (1981): The Adjustment of Stock Prices to Information about Inflation, Journal of Finance, 36 (1), 15-29.

Sharpe, S. A. (1994): Financial Market Imperfections, Firm Leverage, and the Cyclicality of Employment, American Economic Review, 84 (4), 1060-1074.

Stock, J. and Watson, M. (1989): New indexes of coincident and leading economic indicators, in J. Olivier and S. Fisher, eds.: NBER Macroeconomics Annual 1989, Cambridge, Massachusetts.

Stock, J. H. and Watson, M. W. (1999): Forecasting inflation, Journal of Monetary Economics, 44 (2), 293-335.

Veronesi, P. (1999): Stock Market Overreaction to Bad News in Good Times: A rational expectations equilibrium model, Review of Financial Studies, 12 (5), 975-1007.

Vuolteenaho, T. (2002): What drives firm-level stock returns?, Journal of Finance, 57 (1), 233-264.

Table 1 Correlation of Industrial Production Growth with Industry Sale Growth on different Industry Aggregation Levels

	N	Mean	Min	p10	p25	Median	p75	p90	Max
SIC 1-digit Level	8	0.1759	-0.1117	-0.1117	0.0886	0.1621	0.2807	0.4565	0.4565
SIC 2-digit Level	60	0.1836	-0.2446	0.0084	0.0601	0.1415	0.2983	0.4416	0.5439
SIC 3-digit Level	161	0.1604	-0.3835	-0.0247	0.0395	0.1440	0.2802	0.4024	0.6485
SIC 4-digit Level	181	0.1346	-0.3830	-0.0567	0.0198	0.1018	0.2541	0.3854	0.5997
Fama French 48	45	0.1948	-0.1254	-0.0243	0.0817	0.1633	0.3037	0.4813	0.6856

This table contains results of the correlation of year-over-year growth in industrial production with year-over-year growth in industry sales. Industries are aggregated on SIC 1-digit to SIC 4-digit level and on Fama-French 48 industry portfolios level. We used all firms available in Compustat tapes for the industry sales aggregation and the calculation of the correlation. After that we eliminated industries not containing S&P 500 firms and marked firms with a correlation above the median as cyclical.

Table 2 Return Statistics of Individual S&P 500 Firms

Panel A : S&P 500 Firm Returns on Announcement and Non-Announcement Days

	N	Mean	Sd
Non-Announcement Days	4.697.865	0.0550	2.2224
Announcement Days	235.185	0.0704	2.2058

Panel B : S&P 500 Firm Returns on Announcement Days only conditional on the Business Cycle

	N	Mean	Sd
Expansion	171.306	0.0812	2.1031
Contraction	60.600	-0.0053	2.4217

Panel C : Returns of Cyclical and Non-Cyclical Firms on Announcement Days

	N	Mean	Sd
Cyclical	139.896	0.0679	2.2709
Non-Cyclical	92.010	0.0445	2.0639

This table contains return statistics for the individual S&P 500 firms for the time period of May 1967 to Decemeber 2007. Panel A displays returns on on announcement days and non-announcement days. Panel B displays the individual S&P 500 returns only on announcement days but conditions on the business cycle according to the CFNAI classification scheme. Additionally Panel C shows the individual S&P 500 returns on announcement days only conditional on firm cyclicality. A firm is marked cyclical if the correlation of SIC 2-digit industry sales growth with industrial production growth is above the median of all correlations.

Table 3 Return Statistics of Cyclical and Non-Cyclical S&P 500 Firms

	Cyclical	Non-Cyclical
Expansion	0.0903	0.0674
Contraction	0.0041	-0.0195
Good News	-0.0068	-0.0115
Bad News	0.1474	0.1047

This table contains return statistics for the individual S&P 500 firms for the time period of May 1967 to Decemeber 2007. Returns are displayed for announcement days only and conditional on firm cyclicality as well as conditional on the business cycle and the news type. A firm is marked cyclical if the correlation of SIC 2-digit industry sales growth with industrial production growth is above the median of all correlations. The business cycle classification is according to the CFNAI classication scheme. The news type indicates the sign of the unemployment rate surprise. Good news suggest an actual UN rate lower than expected and therefore a negative surprise.

Table 4 Comparison of the NBER, XRIC and CFNAI Classification Scheme for Business Cycles

NBER			XRIC			CFNAI		
Period	# Recession Months	# Boom Months	Period	# Recession Months	# Boom Months	Period	# Recession Months	# Boom Months
05/1967 - 12/1969	-	32	05/1967 - 12/1969	-	32	05/1967 - 12/1969	-	32
01/1970 - 11/1970	11	-	01/1970 - 06/1970	6	-	01/1970 - 12/1970	12	-
12/1970 - 11/1973	-	36	07/1970 - 08/1970	-	2	01/1971 - 07/1974	-	43
12/1973 - 03/1975	16	-	09/1970 - 11/1970	3	-	08/1974 - 07/1975	12	-
04/1975 - 01/1980	-	58	12/1970 - 01/1974	-	38	08/1975 - 02/1980	-	55
02/1980 - 07/1980	7	-	02/1974 - 04/1974	3	-	03/1980 - 09/1980	7	-
08/1980 - 07/1981	-	12	04/1974 - 07/1974	-	3	10/1980 - 08/1981	-	11
08/1981 - 11/1982	16	-	08/1974 - 05/1975	10	-	09/1981 - 02/1983	18	-
12/1982 - 07/1990	-	92	06/1975 - 03/1980	-	58	03/1983 - 06/1989	-	76
08/1990 - 03/1991	8	-	04/1980 - 07/1980	4	-	07/1989 - 12/1992	42	-
04/1991 - 03/2001	-	120	08/1980 - 08/1981	-	13	01/1993 - 12/2000	-	96
04/2001 - 11/2001	8	-	09/1981 - 01/1982	5	-	01/2001 - 10/2003	34	-
12/2001 - 12/2007	-	73	02/1982 - 03/1982	-	2	11/2003 - 11/2007	-	49
			04/1982 - 12/1982	9	-	12/2007 - 12/2007	1	-
			01/1983 - 06/1989	-	78			
			07/1989 - 07/1989	1	-			
			08/1989 - 09/1990	-	14			
			10/1990 - 04/1991	7	-			
			05/1991 - 03/2001	-	119			
			04/2001 - 06/2001	3	-			
			07/2001 - 08/2001	-	2			
			09/2001 - 11/2001	3	-			
			12/2001 - 09/2002	-	10			
			10/2002 - 10/2002	1	-			
			11/2002 - 03/2003	-	5			
			04/2003 - 04/2003	1	-			
			05/2003 - 12/2003	-	8			
# of Recessions	6			13			7	
# of Expansions	7			14			7	
# of Rec./Boom Months	66	423		56	384		126	362
Average Duration	11	60		4	27		18	52

This table contains information about our business cycle measures. The expansion/recession periods as well as the corresponding number of month are displayed for the NBER, XRIC (binary) and the CFNAI (binary) business cycle classification scheme. The bottom line of table 4 contains the corresponding summary statistics.

Table 5 Impact of Unemployment Rate News on Individual Firm Returns

$$ret_{i,t} = \alpha + \beta_1 \cdot D_t^{rec} \cdot S_t^{UN} + \beta_2 \cdot \left(1 - D_t^{rec}\right) \cdot S_t^{UN}$$
$$+ \beta_3 \cdot D_t^{rec} \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_4 \cdot \left(1 - D_t^{rec}\right) \cdot D_i^{cyclical} \cdot S_t^{UN}$$
$$+ \beta_5 \cdot BtM_{i,t} + \beta_6 \cdot MC_{i,t} + u_t$$

	restricted I	unrestricted I	restricted II	unrestricted II
Intercept	0.074***	0.074***	0.023**	0.023**
UN^{rec}	-0.418***	-0.289***	-0.422***	-0.288***
UN^{exp}	0.422***	0.317***	0.496***	0.404***
$Cyclical^{rec}$		-0.211***		-0.219***
$Cyclical^{exp}$		0.172***		0.149***
BtM			0.069***	0.070***
MC			0.001***	0.001***
N	231.906	231.906	204.898	204.898
adj. R2	0.002	0.002	0.003	0.003
LR Chi^2	19.11		14.79	
Prob > Chi^2	0.000		0.001	

This table contains results of the regression of firms daily returns on announcement days ($ret_{i,t}$) on surprises in the unemployment rate (UN) conditional on the state of the economy for the time period of May 1967 to December 2007. Recessions and expansions are defined following the CFNAI classification scheme. Firms are marked as cyclical if the correlation of the year-over-year sales growth rate at the SIC 2-digit industry level with the year-over-year growth rate of industrial production is above the median correlation. The model is estimated restricted and unrestricted concerning the cyclicality coefficients. Robust standard errors are estimated by accounting for clustering at the company level. Significance levels are indicated as follows: *** 1% significance,** 5% significance, * 10% significance. LR Chi^2 denotes the Likelihood-ratio test statistic for the assumption that the restricted model is nested in the unrestricted. Prob denotes the significance level for the LR Chi2 test statistic.

Table 6 Impact of Unemployment Rate News on Individual Firm Returns considering different Business Cycle Measures

$$ret_{i,t} = \alpha + \beta_1 \cdot D_t^{rec} \cdot S_t^{UN} + \beta_2 \cdot \left(1 - D_t^{rec}\right) \cdot S_t^{UN} + \beta_3 \cdot D_t^{rec} \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_4 \cdot \left(1 - D_t^{rec}\right) \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_5 \cdot BtM_{i,t} + \beta_6 \cdot MC_{i,t} + u_t$$

	CFNAI	NBER	XRIC
Intercept	0.023**	0.020*	0.021*
UN^{rec}	-0.288***	-0.333***	-0.342***
UN^{exp}	0.404***	0.303***	0.283***
$Cyclical^{rec}$	-0.219***	-0.211**	-0.216**
$Cyclical^{exp}$	0.149***	0.099**	0.082*
BtM	0.070***	0.074***	0.070***
MC	0.001***	0.001***	0.002***
N	204.898	204.898	185.816
adj. R2	0.003	0.002	0.002
LR Chi^2	14.79	8.43	5.26
Prob > Chi^2	0.001	0.015	0.072

This table contains results of the regression of firms daily returns on announcement days ($ret_{i,t}$) on surprises in the unemployment rate (UN) conditional on the state of the economy. Recessions and expansions are defined according to the CFNAI classification scheme. Firms are marked as cyclical if the correlation of the year-over-year sales growth rate at the SIC 2-digit industry level with the year-over-year growth rate of industrial production is above the median correlation. Robust standard errors are estimated by accounting for clustering at the company level. Significance levels are indicated as follows: *** 1% significance,** 5% significance, * 10% significance. LR Chi2 denotes the Likelihood-ratio test statistic for the assumption that the restricted model is nested in the unrestricted. Prob denotes the significance level for the LR Chi2 test statistic.

Table 7 Impact of Unemployment Rate News on Individual Firm Returns considering different Macro-Growth Proxies

$$ret_{i,t} = \alpha + \beta_1 \cdot D_t^{rec} \cdot S_t^{UN} + \beta_2 \cdot \left(1 - D_t^{rec}\right) \cdot S_t^{UN} + \beta_3 \cdot D_t^{rec} \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_4 \cdot \left(1 - D_t^{rec}\right) \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_5 \cdot BtM_{i,t} + \beta_6 \cdot MC_{i,t} + u_t$$

	GDP	IP	DGO
Intercept	0.022**	0.023**	0.023**
UN^{rec}	-0.237***	-0.288***	-0.309***
UN^{exp}	0.412***	0.404***	0.431***
$Cyclical^{rec}$	-0.348***	-0.219***	-0.204***
$Cyclical^{exp}$	0.156***	0.149***	0.116**
BtM	0.070***	0.070***	0.070***
MC	0.001***	0.001***	0.001***
N	204.898	204.898	204.898
adj. R2	0.003	0.003	0.003
LR Chi^2	29.10	14.79	11.57
Prob > Chi^2	0.000	0.001	0.003

This table contains results of the regression of firms daily returns on announcement days ($ret_{i,t}$) on surprises in the unemployment rate (UN) conditional on the state of the economy. Recessions and expansions are defined according to the CFNAI classification scheme. Firms are marked as cyclical if the correlation of the year-over-year sales growth rate at the SIC 2-digit industry level with the year-over-year growth rate of the real GDP (GDP), the industrial production (IP) or the durable goods orders (DGO) is above the median correlation. Robust standard errors are estimated by accounting for clustering at the company level. Significance levels are indicated as follows: *** 1% significance,** 5% significance, * 10% significance. LR Chi2 denotes the Likelihood-ratio test statistic for the assumption that the restricted model is nested in the unrestricted. Prob denotes the significance level for the LR Chi2 test statistic.

Table 8 Impact of Unemployment Rate News on Individual Firm Returns considering different Industry Aggregation Levels

$$ret_{i,t} = \alpha + \beta_1 \cdot D_t^{rec} \cdot S_t^{UN} + \beta_2 \cdot \left(1 - D_t^{rec}\right) \cdot S_t^{UN} + \beta_3 \cdot D_t^{rec} \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_4 \cdot \left(1 - D_t^{rec}\right) \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_5 \cdot BtM_{i,t} + \beta_6 \cdot MC_{i,t} + u_t$$

	SIC 1-digit	SIC 2-digit	SIC 3-digit	SIC 4-digit	FF 48
Intercept	0.023**	0.023**	0.023**	0.023**	0.023**
UN^{rec}	-0.130	-0.288***	-0.321***	-0.307***	-0.327***
UN^{exp}	0.341***	0.404***	0.438***	0.432***	0.407***
$Cyclical^{rec}$	-0.367***	-0.219***	-0.187**	-0.191**	-0.166**
$Cyclical^{exp}$	0.194***	0.149***	0.107**	0.105**	0.155***
BtM	0.069***	0.070***	0.070***	0.070***	0.070***
MC	0.001***	0.001***	0.001***	0.001***	0.001***
N	204.898	204.898	204.898	204.898	204.898
adj. R2	0.003	0.003	0.003	0.003	0.003
LR Chi^2	23.38	14.79	9.82	9.58	12.40
Prob > Chi^2	0.000	0.001	0.007	0.008	0.002

This table contains results of the regression of firms daily returns on announcement days ($ret_{i,t}$) on surprises in the unemployment rate (UN) conditional on the state of the economy. Recessions and expansions are defined following the CFNAI classification scheme. Firms are marked as cyclical if the correlation of the year-over-year sales growth rate at the SIC 1-digit industry level to SIC 4-digit industry level as well as the Fama French 48 industry classification level with the year-over-year growth rate of the the industrial production is above the median correlation. Robust standard errors are estimated by accounting for clustering at the company level. Significance levels are indicated as follows: *** 1% significance,** 5% significance, * 10% significance. LR Chi2 denotes the Likelihood-ratio test statistic for the assumption that the restricted model is nested in the unrestricted. Prob denotes the significance level for the LR Chi2 test statistic.

Table 9 Impact of Unemployment Rate News on Individual Firm Returns considering different Unemployment Rate Surprises

$$ret_{i,t} = \alpha + \beta_1 \cdot D_t^{rec} \cdot S_t^{UN} + \beta_2 \cdot \left(1 - D_t^{rec}\right) \cdot S_t^{UN} + \beta_3 \cdot D_t^{rec} \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_4 \cdot \left(1 - D_t^{rec}\right) \cdot D_i^{cyclical} \cdot S_t^{UN} + \beta_5 \cdot BtM_{i,t} + \beta_6 \cdot MC_{i,t} + u_t$$

	MMS	HB	BHJ^{long}	BHJ
Intercept	0.005	0.023**	0.023**	0.014
UN^{rec}	-0.340***	-0.288***	-0.333***	-0.496***
UN^{exp}	0.400***	0.404***	0.458***	0.662***
$Cyclical^{rec}$	-0.497***	-0.219***	-0.334***	-0.313***
$Cyclical^{exp}$	0.128	0.149***	0.076	0.151*
BtM	0.036**	0.070***	0.068***	0.070***
MC	0.001***	0.001***	0.001***	0.002***
N	154.725	204.898	204.898	183.268
adj. R2	0.002	0.003	0.003	0.004
LR Chi^2	20.23	14.79	16.29	12.18
Prob > Chi^2	0.000	0.001	0.000	0.002

This table contains results of the regression of firms daily returns on announcement days ($ret_{i,t}$) on surprises in the unemployment rate (UN) conditional on the state of the economy. Recessions and expansions are defined following the CFNAI classification scheme. Firms are marked as cyclical if the correlation of the year-over-year sales growth rate at the SIC 2-digit industry level with the year-over-year growth rate of industrial production is above the median correlation. The model is estimated using four different unemployment rate surprises. The surprises using initial, unrevised date ("HB"), the original surprises we obtained from Boyd, Hu, and Jagannathan (2005) ("BHJ") and the surprises drawn from Money Market Services ("MMS"). Additionally we show the results with surprises from the forecasting model using unrevised date for our extended period from May 1967 to December 2007 (BHJ^{long}). Robust standard errors are estimated by accounting for clustering at the company level. Significance levels are indicated as follows: *** 1% significance,** 5% significance, * 10% significance. LR Chi2 denotes the Likelihood-ratio test statistic for the assumption that the restricted model is nested in the unrestricted. Prob denotes the significance level for the LR Chi2 test statistic.