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Asymmetric Relationships and the Cross Section of Stock Returns

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Abstract

This thesis consists of two different papers within the field of Asset Pricing, which study asymmetric relationships in the Cross-Section of Stock Returns: "State Dependence of Macroeconomic Announcement Betas and the Cross-Section of Stock Returns" and "Idiosyncratic Higher Order Moments in the Cross-Section of Stock Returns". In the first paper I examine the relationship between macroeconomic data releases and stock prices. Using an Event Study approach and regressing individual stock returns on an estimate for the unexpected component of different macroeconomic announcements, I find that stocks do not show a significant reaction to unexpected announcement values on average. The average reaction is however statistically different from 0. Moreover the reaction is highly dependent on the state of the economy. In the second paper I examine the relationship between the idiosyncratic higher order moments, skewness and kurtosis, and mean returns. I do a number of different sorting procedures where I sort stock according to their estimated skewness and kurtosis. I find that a portfolio consisting of stocks with higher idiosyncratic skewness has a higher mean return. This pattern is monotonic through the sorted portfolios and robust to controlling for other variables by double- and triple-sorting.

Key Words: Asymmetry, Idiosyncratic Skewness, Higher Order Moments, State Dependence, Macroeconomic News

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Contents

1 State Dependence of Macroeconomic Announcement Betas and the Cross-Section of Stock Returns

Abstract

I examine the relationship between macroeconomic data releases and stock prices. The study takes the form of an event study and examines the responses of each individual stock in the US equity universe to the unexpected component of macroeconomic data releases. The unexpected component of a release is estimated using Money Market Services' market surveys and for interest rates decisions it is estimated using price changes of Federal Funds Futures. The analysis is then extended to explain the responses of individual stocks using a set of firm-specific variables. In a third step the analyzed securities are sorted with respect to their announcement betas to examine whether stocks with high sensitivity to macroeconomic announcements earn a higher return. None of the data releases produce a significant beta for more than 20 percent of the stocks nor are the betas significant on average. The sample of estimated betas is however significantly different from zero. In addition, when allowing for different reactions in expansions and contractions, through the use of state-dummies, the difference between the responses turn statistically significant for all the analyzed announcement types. Furthermore, the second step regressions suggest that large firms and value firms are less sensitive to macroeconomic announcements. However, the portfolios sorted on announcement betas do not show a significant spread from high to low.

1.1 Introduction

The relationship between the real economy and asset prices has been one of the most debated issues within the literature in finance and economics for many years, see for example Chen, Roll and Ross (1986) or Fama (1991). The link between the two plays a crucial role in important financial models such as the Intertemporal Capital Asset Pricing Model (ICAPM) by Merton (1973) and the consumption-based Lucas-Model, Lucas (1978). Any causal link has been hard to establish and the lack of knowledge has created a number of puzzles at the intersection between finance and macroeconomics which are hard to explain, see for example Campbell (2003) for a list of the most common puzzles.

The analysis of stock responses to macroeconomic announcements is an area that has managed to uncover some parts of the relationship between asset prices and economic fundamentals. The literature has established relationships between bond yields and macroeconomic announcements, see, for example, Rigobon and Sack (2008). The same is true of other asset classes, such as commodities, currencies and to some extent equity indices. Faust et al. (2003) analyze how monetary decisions impact exchange rates, Frankel (2008) analyzes how monetary shocks affects commodity prices, and Boyd and Jagannathan (2005) analyze the relationship between stock indices and unemployment news. Not only have the responses of prices been studied, but also how the volatility of asset returns co-varies with macroeconomic announcements as in Ederington and Lee (1993).

The effect on equity indices has in general been hard to establish, because announcements affect stock prices in two different ways. If we use the traditional asset pricing equation to decompose the main factors that drive the prices of financial assets, we can gain insight as to why a study on individual stock returns instead of equity indices can help us better understand equity index movements and stock responses in general when the economy is hit by unexpected news:[1]

$$p_t = E_t(x_{t+1}, m_{t+1}) \tag{1}$$

In equation (1), p_t is defined as the price of the asset at time t, x_{t+1} defined as the asset pay-off, and m_{t+1} is defined as the stochastic discount factor. For equities the pay-off is the stream of future dividends. The amount of dividend is dependent on, and varies with, the fortunes of the specific

[1] Please refer to, for example, Cochrane (2005) for a theoretical motivation of the standard asset pricing equation.

company which has issued the stock. How well a company performs financially depends in its turn on the economy at large as well as on a number of idiosyncratic factors. The stochastic discount factor is determined by some unspecified function dependent on the interest rate.

As an example of how Macroeconomic Announcements affect the different components of the pricing equation for stocks, if the Census Bureau (CB) reports increases in Retail Sales above forecast, it will often increase the expectations of the future performance of the economy, both by the Federal Open Market Committee (FOMC) and by investors. The higher expectations increase the likelihood that the FOMC will counteract it, with a monetary policy that increases interest rates, to "cool down" the economy and hence decrease the stochastic discount factor. A decrease of the stochastic discount factor will, ceteris paribus, decrease all asset prices. A better performing economy will usually also increase the expectations about dividends for stocks. Therefore the two variables in the asset pricing equation could work in different directions for equity prices.

With the decomposition described above it is not surprising that it has been hard to detect a clear pattern on how economic news affects stock prices in general. Most studies, for example, McQueen and Roley (1993), Bernanke and Kuttner (2005), and Rigobon and Sack (2008), have been conducted on equity indices and not on individual stocks. In general, firms have very different characteristics and good macroeconomic news for a specific stock could be bad news for another stock. So not only could the two variables in the asset pricing equation work in different directions for stock indices, the impact on future dividends, should also be different from stock to stock.

In a recent paper, Cenesizoglu (2011) found evidence that portfolios constructed by sorting on firm characteristics, book-to-market value and size, react differently to different macroeconomic announcements. Given the complicated nature of stock reactions and the evidence found by Cenesizoglu, I extend his analysis from portfolios sorted on firm characteristics to an analysis on individual stocks. Bestelmeyer and Hess (2012) perform a similar exercise and find that individual firms with sales highly correlated with the business cycle react more strongly to unexpected announcements from the Employment Report. This thesis will also be an extension of their work, primarily their data sample, since they only use employment news and the stock return for each firm in the S&P500 index.

The use of individual stocks allows me to study which announcements that do not affect equity indices because stock prices are unaffected and which announcements that do not affect equity indices because the constituents of the indices react differently. With estimated betas for each stock I will also try to specify why different stocks react differently to different announcements.

If individual stocks react strongly to the unexpected component of macroeconomic announcements it could be because these stocks are more exposed to some unspecified risk factor. For example, if the price of a stock decreases more than for other stocks, when an important macroeconomic indicator comes in below expectations, and increases more than for other stocks when the same indicator is reported above expectations, it suggests that this stock has an inherited, above average sensitivity to the economic environment. Since investors seek to hold stocks that outperform in a bear market to hedge their exposures, a stock with a high sensitivity to the macroeconomic environment should earn a risk premia for its inability to hedge market turns. Using the estimated betas for each stock, I will examine this conjecture and test whether the sensitivity to macroeconomic announcements could proxy for some unspecified risk factor that causes stocks with high announcement betas to earn a higher return than those with a low announcement beta.

The relationship between macroeconomic announcements and stock returns is important for a number of different fields. It could add value within asset pricing in terms of a deeper understanding of which risks that reward investors and when the risks are most important. It could also add value in risk management and portfolio management through a better knowledge of what drives stock prices in connection to macroeconomic announcements and macroeconomic conditions.

When examining the relationship between macroeconomic announcements and stock prices, I regress stock returns, using the US equity universe, on the unexpected component of the announcements to estimate how the stocks react to macroeconomic news. I use Money Market Services' (MMS) market surveys to estimate the market's expectation of macroeconomic indicators: Retail Sales, Trade Balance, Inflation (more specifically core PPI), Employees on Non-Farm Payrolls, the Unemployment Rate, the Institute for Supply Management's (ISM) Manufacturing Index, the Consumer Confidence Index, Housing Starts, New Home Sales, Industrial Production, and advance GDP. To estimate market expectations on interest rate decisions I use prices on Federal Funds Futures. I then define the unexpected component of a macroeconomic announcement as the difference between the reported value and my estimate of the market's expectation. The regression is estimated for all stocks, the twelve macroeconomic announcements mentioned above, and an aggregation of the announcements. I will use two different regression specifications. The first specification estimates the stock responses in general, and the second specification uses dummy-variables for the state of the economy, to allow for different reactions during expansions and contractions. Five different time-periods will be used: the full time-period from 1990 to 2011 as well as four sub-periods.

I find that neither individual announcements nor aggregated announcements significantly affect stock prices on average. However, I do find evidence that a stock index reacts significantly to the unexpected component of releases of Retail Sales and Trade Balance when using the full time-period. Retail Sales also cause a significant stock reaction in the latest sub-period, which is 2006-2011, of the data sample. Even though the betas are not significant on average for individual stocks, I find that the average beta is significantly different from zero. This is true for all different announcements using the full time-period. What is perhaps more interesting is that the signs of the average beta are not consistent over time-periods. This suggests that the reaction of stocks is dependent on some time-varying factor, such as the state of the economy.

This conjecture is confirmed in the second specification with expansion- and contraction-dummies. The estimated betas are significantly different for expansions and contractions for all announcements except Employees on Non-Farm Payrolls and New Home Sales. The largest and most significant differences are found for Retail Sales, Housing Starts and the Federal Funds Rate. For the Federal Funds Rate, stocks react positively when the targeted rate is lower than expected during recessions while the reaction is insignificant in expansions. For Retail Sales and Housing Starts, stocks react positively to reported values above expectations in recessions and negatively to reported values above expectations during expansions.

Using the estimated betas from all sub-period regressions, for each of the announcements, I regress the betas on a set of firm characteristics and time-period dummies. The variables for firm characteristics are: Acid-ratio, Debt-to-equity, Book-to-Market, a proxy for market illiquidity (Illiq),[2] and the log of market value. In these regressions, the size and book-to-market are significant for inflation and Trade Balance. Large firms and value-firms have announcement betas closer to zero. Otherwise, the coefficients for firm characteristics have different signs and magnitude, depending on which first-step regression the betas are taken from. Each variable is significant at a 5 percentage level for one set of betas. With the estimated betas from the first step regressions, portfolios are

[2] See Chapter III. Section A.iii. for the definition of the variable Illiq.

constructed by sorting stocks with respect to their beta and dividing them into 10 ranked deciles. This sorting procedure is repeated in rolling 5-year periods. The average return for each portfolio, both contemporaneously and out-of-sample, is then calculated for each time-period and eventually averaged across the time-periods used. No clear pattern is found and the spread from high to low is insignificant for all announcement betas.

The structure of the remainder of the thesis is as follows. Chapter II summarizes related literature on macroeconomic announcements and individual stock reactions to news. Chapter III presents the empirical framework. I present the data and each of the testing methods are explained and discussed. Chapter IV presents the results from the empirical exercises and Chapter V concludes the paper.

1.2 Related Literature

This chapter will present the main findings in the related literature. The literature on the relationship between macroeconomic announcements and asset returns will be presented in Section A. The literature on stock reactions to firm-specific news will be covered in Section B. In Section C, the recent literature of the relationship between firm-characteristics, stock returns and macroeconomic announcements will be summarized. Both empirical findings and methodology will be discussed.

1.2.1 Macroeconomic Announcements

As summarized in the Introduction, a number of studies have been conducted on the effects of announcements on commodities, currencies, equity indices and government bonds. McQueen and Roley (1993) were among the first to find evidence that some news impact stock returns if the empirical framework allows for estimating different responses depending on the state of the economy. They conclude that stocks react differently to macroeconomic announcements depending on the announcements effect on the expectation of future cash flow, the effect on the discount factor and the state of the economy. They find that good news about real economic activity is bad news for the stock market during expansions while monetary news affect stock prices independently of the economic state. Rigobon and Sack (2008) use two different empirical frameworks to analyze the effects of announcements on the S&P 500 and Treasury Bonds with four different maturities. They use the Event Study-approach and a new approach they label Identification Through Censoring (IC). In the Event Study-approach they first estimate market expectations using MMS market surveys, then they define the unexpected component as the difference between the reported value and the expected value. They then regress returns, of the day of announcements, on the unexpected components of data releases. After this exercise they argue that the results may be subject to bias if one aim to examine the responses of asset prices to “true” macroeconomic surprises. In other words, a reported value may miss some other information contained in a released report that carries importance for asset prices and/or contain information that is not relevant. This in turn creates biased estimators. They try to go around, or solve, this problem with the IC-approach. They use the estimated return variance for the studied asset in periods without announcements and compare it to the return variance of the days with announcements to pin down how much of return movements that are noise and which are a result of the announcement.[3] Furthermore they also use different definitions of the return, both the daily return and the 25 minute return directly after the data release. The smaller time window is used to minimize reactions not related to the actual data release. For bond prices they find that all announcements have a significant effect whilst they only find that inflation (both as PPI and CPI) and Hourly Earnings have an effect on the S&P 500. In both these cases the effect is negative. The results suggests that higher than expected inflation generates a negative return for the S&P 500. With the IC framework they manage to find much higher coefficients when analyzing the effects of macroeconomic announcements on equity returns. Hourly Earnings, Inflation, Durable Goods, ISM, New Home Sales and Housing Starts all have a negative effect whilst Non-Farm Payrolls, GDP, Retail Sales, Capacity Utiliziation, Chicago Purchasing Manufacturers Index and Consumer Confidence have a positive effect. They do however conclude that the IC approach do not change the patterns of reactions found using the Event Study-approach, but only the magnitude. They also note that their estimates of the noise contained in the reported value are likely to be too high, which would explain the large differences in magnitude between the two approaches.

Flannery and Protopapadakis (2002) find that six different macroeconomic news releases impact aggregate stock returns. Using a GARCH model for the daily stock market, in which both equity returns and their conditional volatility are allowed to vary with macroeconomic announcements, they find that the real variables Trade Balance, the Employment Report and Housing Starts affect stock returns as well as the nominal variables CPI, PPI and money growth. The nominal variables were found to be negatively related to stock prices whilst the real variables only affected prices through increased conditional volatility. Andersen et al. (2003) find evidence that releases impact prices of currencies and that the reactions are asymmetric, negative releases (below or above expectations depending on which macroeconomic indicator that is used) have a greater impact than positive releases. Brenner, Pasquariello and Subrahmanyam (2009) study the volatility, co-movements and returns for stock indices and bonds. They find the opposite asymmetric relationship to be true for stock returns, with larger reactions to positive news. For volatility the relationship is reversed. They also find Non-Farm Payrolls to be the most important indicator in the Employment Report released by The Bureau of Labor Statistics. The unemployment rate and other indicators included in the Employment Report do not impact stock returns to the same extent. Balduzzi, Elton and Green

[3] Please refer to Rigobon and Sack (2008) for a detailed description of the method.

(2001) examines the effect 17 different macroeconomic announcements have on the price, volume and bid-ask spread for Government Bonds with different maturities. They find significant effects for all 17 announcements for at least one of the scrutinized maturities. This implies that different macroeconomic announcements convey information for different horizons. On the microstructure side, volatility and volume show persistent increases while bid-ask spreads show an initial hike and then returns to normal values shortly afterwards. Bernanke and Kuttner (2005) documents negative reactions of stock indices to Federal Funds Rate hikes, a 25 basis points unanticipated increase in the Federal Funds Rate results in a 1 percent decrease in stock indices. They analyze both the reaction to the news release itself and the reaction to the unanticipated, and thus un-priced, portion of the news release. In line with the Efficient Market Hypothesis, Fama (1965) and Samuelson (1964), they find that the reaction is only significant to unanticipated changes.

Boyd, Hu and Jagannathan (2005) analyze their results one step further by studying how the unemployment news effect stock returns when return movements are decomposed into expectations of future dividends and the discount factor. They find that bad unemployment news results in positive stock reactions in good states of the economy and negative stock reactions in bad states of the economy. They argue that in expansions, stocks are most dependent on news affecting the interest rates. While in contractions, news about the general state of the economy, that impacts future dividend growth, are the most important. That is, rising unemployment in a recession primarily impact stock returns through the expectation of future dividends. Therefore, during recessions, good news of employment is good news for stock prices. On the other hand, in expansions, rising unemployment is an indication of the economy getting worse or failing to pick up steam which increases the probability of a loose monetary policy from the FED. Hence, during expansions, unexpected bad news translates into a higher discount factor and higher prices. Contradictory to the results of Boyd, Hu and Jagannathan (2005), Poitras (2004) do not find that the responses of stock returns to macroeconomic announcements are state dependent. He examines a large number of different variables and cannot find robust and significant evidence for state dependent effects for any of them. The results differ depending on if a forward-looking or backward-looking definition of economic states is used. Gilbert (2011) analyzes the connection between returns on announcement days and the revisions for announcements made at a later date. He finds that the link differs across business cycles with a positive relationship in expansions and negative relationship in recessions. He also finds that releases closer to the revised values affected stock returns more. This suggests that investors do not only respond to the release value but also to the information it conveys about future revisions. Gilbert, Scotti, Strasser and Vega (2010) analyzes how the timeliness of announcements within an announcement cycle affects estimated responses and find that early announcements, in general, have higher effects on stock returns. Implying that some of the information released in later announcements during the cycle has already been discovered and priced during the first part of the same announcement cycle. Their study focuses on the Treasury Bond Market.

Khimilevska (2006) on the other hand tries to confirm that macroeconomic announcements are systematic risk factors. She incorporates jumps in an ICAPM to observe how announcements affect stock returns. She finds that almost all jumps in the Sharpe-ratio are related to macroeconomic announcements.[4] The jumps are of greater magnitude during expansions. Trade Balance is the announcement that experiences the greatest jumps in the Sharpe-ratio. Savor and Wilson (2012) analyze how the market risk premia co-varies with announcement days. They find evidence that announcement days have much higher risk premia than non-announcement trading days. Trading days with announcements for CPI, PPI, GDP, FOMC decisions and the Employment report captures 60 percent of the yearly risk premia while it only covers 13 percent of trading days. The higher equity return cannot be explained by higher volatility since it is only marginally higher on announcement days, which in turn leads to a 10 times higher Sharpe-ratio on these announcement days than on other trading days. Interestingly they also find the same relationship when controlling for the forecasted value of the announcements, suggesting that it is not the information in itself that make returns higher but the risk of negative news. They conclude that the results are explained by time-varying risk premia which jumps during announcement days which, in general, contain much higher systematic risk than other trading days.

1.2.2 Firm-specific Announcements

There has also been a large body of research on how individual stocks react to firm-specific news. Beaver (1968) was the first to show that firms experience abnormal returns in times of earnings announcements.[5] Chari, Jagannathan and Ofer (1988) find that small firms had a far higher reaction to earnings announcements than large firms, both in terms of abnormal returns and volatility.

[4] The Sharpe-ratio is defined as excess return divided by the returns standard deviation, Sharpe (1966).

[5] In his paper he defines Abnormal Return as the excess return over the market index return, independent of the market beta-exposure of the firm.

Announcements that took place earlier in the reporting-cycle experienced higher reactions, even though the findings cannot be solely explained by the timing of announcements. This suggests that idiosyncratic earning announcements convey information about the economy as a whole and hence, some components of the information is not idiosyncratic. Kalay and Lowenstein (1988) find that firms also react to their announcements about dividends. Unconditional mean return, variance and systematic risk are higher during periods of dividend announcements. In a recent paper Patton and Verardo (2012) also find that the market beta of a firm increases during earnings announcements. The magnitude of the increase in dependent on the deviation between announced values and forecasts. Given that earning announcements often are regarded as idiosyncratic news, these findings are consistent with theory that either claims that earning announcements reveals important information about priced risk factors or that idiosyncratic risk do matter.[6] They did however also find that the stocks with the closest relationship to the aggregate economy had their beta increased the most, but this relationship could not explain the difference between betas in announcement times and betas in non-announcement times. The uncertainty around announcements also played an important role; the relationship between dispersion in forecasts and increases in announcement-time betas was strong and positive. Savor and Wilson (2011) find similar evidence in the form of higher returns in earnings announcement periods compared to non-earnings announcement periods. They found that a portfolio with long positions in announcing firms and short positions in non-announcing firms could explain the behavior of other portfolios sorted on characteristics. Tetlock (2010) uses firm-specific news to assess how individual stocks react to news. The main finding is that small and illiquid stocks have stronger reactions to news than larger and more liquid stocks. He explains these findings arguing that informed investors have already adjusted to the news before they are public. Leaving uninformed investors to react to news and for large and liquid stocks their beliefs does not have a strong enough impact to significantly move prices. Counter wise, small and illiquid stocks have a smaller portion of informed investors so news about them are to a greater extent "shocks" that many investors get new information from, such that they form new beliefs and prices hence react to a higher extent than for large and liquid stocks.

1.2.3 Macroeconomic Announcements and Firm Characteristics

The first to move the analysis of macroeconomic announcements to the characteristics of firms were Adams, McQueen and Wood (2003). They analyze the response of portfolios sorted on size to

[6] The second theory consistent with the results, that idiosyncratic risk matters, have gained more wide recognition the past years. See for example Goyal and Santa-Clara (2003)

unexpected inflation announcements. They find reactions of a greater magnitude for large stocks. They argue that is because noise embeds the true response for small stocks. They also find the reactions to be greatest when bad news are released in expansions. Andersen et al. (2005c) find that equity betas vary with economic indicators such as Industrial Production. They find this to be primarily true for value-stocks, stocks with a high book-to-market ratio. Cenesizoglu (2011) examines the reactions of portfolios sorted with respect to the firm characteristics size and book-to-market. He finds significant responses to Trade Balance, Retail Sales, Non-Farm Payrolls, Hourly Earnings, Consumer Credit, Housing Starts and Federal Funds Rate and a number of price indices for the size-sorted portfolios. Significant differences between portfolios can however only be detected for the Non-Farm Payrolls announcements. For Book-to-Market sorted portfolios the same announcements are significant with the exception of Consumer Credit. With this procedure he does find significant differences between the portfolios for Non-Farm Payrolls, Retail Sales as well as a couple of price indices. In addition he finds considerable differences in reactions depending on the state of the economy for Non-Farm Payrolls. The reactions to good employment news are negative and significant for large and growth firms in expansions and insignificant in recessions. For small and value firms the return reactions to good employment news are positive in expansions and insignificant in recessions. These differences are robust to the definition of economic states and when controlling for other information released in the Employment Report. Gilbert, Palacios and Wang (2011) analyze individual stocks' reactions to Non-Farm Payrolls. They work under the hypothesis that this specific announcement should be of greater importance to labor-intensive firms than for capital-intensive firms. They do also find that the betas for labor-intensive firms are considerably higher. Moreover, a constructed portfolio that is long stocks with the highest return on announcement days and short stocks that have the lowest return on announcement days is priced in a Fama and McBeth –regression. Arshanapalli , Nelson and Switzer (2010) uses unexpected announcements for Employment, PPI and GDP to observe the reactions of the two Fama and French factor portfolios as well as a Momentum Portfolio that was found to be priced by Jegadeesh and Titman (1993) and Carhart (1997).[7] Each factor portfolio are affected by the announcements, the information from announcements cannot however be fully captured by the factors. Likewise Aretz, Bartram and Pope (2010) find that the portfolios capture exposures to macroeconomic factors and that these factors capture both innovations in expected pay-outs as well as discount rate innovations.

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[7] A Momentum Portfolio consists of long positions in stocks that had a high return the last year and short positions in stocks with low returns the last year.

Bestelmeyer and Hess (2012) document that firms with a high absolute correlation between their sales and the business cycle reacts stronger to the Employment Report than stocks with a lower absolute correlation. They find the relationship using the stocks contained in the S&P 500 index.

1.3 Empirical Framework

Chapter III will present the empirical framework I use to examine the relationship between stock returns and macroeconomic announcements. In section A. the data that is used will be presented and discussed in three steps. In the first step, subsection A.i, the surveys, where the forecasts are collected from, are presented. In the second step, subsection A.ii, the macroeconomic announcements are described. In the third step, subsection A.iii, the explanatory variables used in the second step regression, when an effort to explain why stocks have different betas is made, are presented. In Section B. the method for estimating the unexpected component of the macroeconomic releases is defined and analyzed. Section C. presents and discusses the regression specifications that are used to estimate the announcement betas. Section D. follows with the framework for explaining the betas that are estimated with the regressions in Section C.. Section E. conclude the Chapter with an explanation of the sorting procedure that examines if the announcement betas proxy for some unspecified risk factor.

1.3.1 Data

1.3.1.1 Surveys and Data collection

The forecasts of the macroeconomic variables that are used are collected from MMS's and Bloomberg's surveys. The dataset starts in January 1990 and ends in December 2011. The variables used can be observed in Table 1.

Table 1 - Macroeconomic Announcements

The macroeconomic releases that are used are presented below in Table 1. Information about the releases are presented in columns 2, 3, 4 and 5. Descriptive statistics: the average unexpected announcement value, its standard deviation, and number of observations are presented in columns 6, 7 and 8. In columns 9 through 12, the same descriptive statistics are presented but for the subsamples of expansions and contractions.

Data	Supplier	Frequency	Data Format	Release Time	Avg	Sd.	No. Obs	Expansion		Contraction	
Non-Farm Payrolls	BLS	Monthly	Thou.	08:30	-20,75	101,97	264	-15,67	102,53	-52,77	93,41
GDP (advance)	BEA	Quarterly	p.p	08:30	0,13	0,74	88	0,11	0,75	0,30	0,84
Retail Sales - excl. Auto	CB	Monthly	p.p	08:30	-0,03	0,44	264	-0,04	0,44	-0,04	0,65
Core PPI	BLS	Monthly	p.p	08:30	-0,019	0,25	264	-0,040	0,29	0,072	0,23
Housing Starts	CB	Monthly	p.p	08:30	0,009	0,08	264	0,011	0,08	0,000	0,07
Manufacturing Index	ISM	Monthly	p.p	10:00	0,03	2,03	264	0,06	2,02	-0,15	2,21
Consumer Confidence	Conference Board	Monthly	p.p	10:00	0,16	5,07	264	0,33	4,80	-1,23	6,81
New Home Sales	CB	Monthly	Thou.	10:00	5,66	60,51	264	7,42	63,56	-5,11	38,33
Federal Fund Rate	FOMC	8/year	p.p	14:15	-0,002	0,10	143	0,002	0,13	-0,027	0,10
Trade Balance	BEA	Monthly	Bn	10:00	0,10	4,00	264	-0,03	4,06	0,95	3,73
Unemployment Rate	BLS	Monthly	p.p	08:30	-0,03	0,15	264	-0,04	0,15	0,05	0,16
Industrial Production	Federal Reserve Board	Monthly	p.p	09:15	0,16	0,33	264	0,01	0,29	-0,17	0,52
Aggregate	-	-	Standardized	-	0,04	1,00	2329	0,03	1,02	0,28	1,82

The forecast release from MMS comes the Friday before each data release.[8] The surveys are conducted using telephone interviews and include around 40 money managers. They then report the median forecast for each data release. The MMS surveys have been found, Balduzzi et al. (2001), to be an unbiased estimator of market expectations and more consistent than estimators that model the market's expectation using asset prices and previous data releases as input variables. Lanne (2007) also found that the MMS forecasts measure the market expectations rather well since it does not show any significant deviations from implied forecasts from Binary-Derivatives written on the data release. However both the MMS forecasts and the implied forecast from the derivatives market do a better job forecasting the final release value rather than the first release. For example, forecasts for the advanced GDP report are on average closer to the second revision of GDP (the Final Report), that is reported two months after the advanced report, rather than the release actually forecasted. During the last years, Bloomberg's surveys have been considered as the most important for the financial markets. Because of this, together with the possibility to extend my data sample, I choose to use Bloomberg from 2004 and onwards, as in Rigobon and Sack (2008). Prior to 2000, although considered as an important estimate, the Bloomberg Surveys had a low and variable number of respondents, depending on the macroeconomic release in question. The MMS forecasts have been around for a longer period of time and were more important during the 20th century and are therefore used for the beginning of the sample.

The Bloomberg survey is conducted in a similar fashion in that it surveys a high number of analysts: in 2004 most announcements had around 40 respondents and in 2012 that figure had grown to around 80. The Bloomberg survey does also report the median value of the forecasts. However, they do not conduct the survey at one point in time. Respondents are instead free to submit their forecast at any point. This results in forecasts being submitted starting with two weeks in advance up until the day before the release. This could pose a problem if the reported value was a mean but since it is a median, out of touch forecasts do not generally affect the reported value, since the median in contrast to the mean is independent of outliers. Random controls for all variables were conducted and for all controls a vast majority of forecasts were submitted, at the latest, one week before the data release.

Values for the Federal Funds Rate consist only of values from scheduled Federal Open Market Committee meetings. This is done in order to keep the values as truly exogenous. This would not be

[8] That is a minimum of 3 days prior to the release, when the release is on a Monday, and a maximum of 7 days, when the release is on a Friday.

true for unscheduled meetings and the monetary decisions taken there since unscheduled meetings are inserted because of economic conditions and are hence endogenous.

Below are a brief summary of each of the explanatory variables used in the first and second step-regressions. First, the macroeconomic announcements used when estimating the responses of the stocks are presented. Information about the time of release, the supplier of the release, their importance for the economy and method of estimation are included. Second, financial ratios, characterizing firms, used when explaining the announcement betas estimated in the first step-regressions are presented. The summary includes how they are calculated and their importance to individual firms. Campbell and Sharpe (2007) also showed that consensus survey's, such as MMS, tend to be biased towards the prior months release and that investors are aware of this anchoring bias, Tversky and Kahneman (1974). They show this by examining the reactions of bond prices to the predictable and unpredictable component of the surprise and find that bond yields are only affected by the unpredictable component (when they control for anchoring bias towards the previous months value).

1.3.1.2 Macroeconomic Announcements

Purchasing Managers Index

The indicator is supplied by the Institute for Supply Management (ISM) and Markit Group. They survey purchasing managers for their estimates of goods and services purchased. The responses are then aggregated to form an indicator whether conditions have improved or worsen. An index value of 50 indicates no change while values above indicate an improvement and hence a value below 50 indicates worsened conditions. It is released the first business day of each month.[9] The indicator only surveys the private sector but does so for the whole country why it is preferred to Chicago Purchasing Managers Index, also released by ISM, which only surveys the greater Chicago area.[10]

Consumer Confidence Index

The consumer confidence index is a forward looking indicator which measures the beliefs of consumers about the near term state of the economy. Surveyed consumers provide data and estimates of their current and future consumption and savings. Current conditions, "The Present Situation Index", make up 40 percent of the reported value and beliefs about the future, "The

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[9] For more information about the indicator please visit: http://www.ism.ws/ismreport/

[10] More information about the Chicago Purchasing Manager Index can be found at https://www.ism-chicago.org/insidepages/reportsonbusiness/

Expectations Index", account for the other 60 percent. The report is released by The Conference Board on the last Tuesday of every month. The index has its base value, 100, from 1985.[11]

Retail Sales excluding Autos

The report is released about two weeks after each month's end. It is released by the Census Bureau (CB) of the Department of Commerce. The reported value is the change over the previous year to get rid of seasonality. CB release two values each month, the first is the advance estimator for the last month and the second is a revised estimator for the next to last month. The value that is used in this thesis is the advanced estimator of Retail Sales excluding automobile sales. Retail Sales is a measure of consumer demand. The figure reported is collected through a mail-survey of around 5,000 companies. Of those 5,000 companies, 1,300 companies that have a large impact on retail sales are surveyed each month while the other 3,700 companies are randomly selected.[12]

Inflation

There are a number of releases that measures inflation. The first one released each month is the Producer Price Index (PPI). A couple of days later, the Consumer Price Index (CPI) is released. The reported value of PPI does often impact the beliefs of CPI. Since many of the forecasts are submitted for the CPI before the release of PPI, it can cause inconsistencies between the reported forecast and the true market expectations. Therefore PPI is used for this thesis even though CPI is the more popular measure of inflation. The core PPI is released by the Bureau of Labor Statistics (BLS) of the Department of Commerce in the middle of each month.[13] Arshanapalli, Nelson and Switzer (2010) also argues that since unexpected inflation, in the form of PPI, is such a major determinant of interest rate decisions that they can exclude interest rate decisions from their analysis.

Gross Domestic Product

There are three major releases of Gross Domestic Product (GDP) figures; the advance report, the preliminary report and the final report. Since the advance GDP report is the least backward-looking variable and the one which it can be argued to carry most information, it will be used for this thesis.

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[11] More information on the Consumer Confidence Index can be found at http://www.conference-board.org/data/consumerconfidence.cfm
[12] More information about Retail Sales can be found at http://www.census.gov/retail/marts/about_the_surveys.html
[13] More information about the PPI can be found at http://www.bls.gov/ppi/

The reports are released by the Bureau of Economic Analysis (BEA) of the Department of Commerce.

Unemployment

There are various figures that can be used for unemployment. The most important figure has in prior literature been found to be Employees on Non-Farm Payrolls (Brenner, Pasquariello and Subrahmanyam, 2009). It is released the first Friday of each month by BLS of the Department of Labor. It is a component of the Employment Report which includes a number of other indicators. The fact that the indicator is only one of a number of indicators released simultaneously can cause problems when estimating the effect of employment news on stock returns. If Employees on Non-Farm payrolls comes in above expectations, i.e. good news, while another indicator, such as unemployment rate, is reported above expectations, i.e. bad news, the beta estimation for Employees on Non-Farm Payrolls would be biased. A multiple regression will also be estimated where the responses of stocks are measured for both Non-Farm Payrolls and the Unemployment Rate. Comparing the results from both procedures will give information to what extent the above problem is present in the standard procedure. [14]

Balance of Trade

To measure the impact of the Balance of Trade report, Trade Balance is used. The trade balance is released by the BEA of the Department of Commerce. It is the difference between exports and imports of goods and services of the next to last month and is released the second Thursday each month.[15]

Housing Market

I will include two announcements for the housing market; New Home Sales and Housing starts. New Home Sales is released by the Census Bureau. It measures the sales of newly constructed single-family houses. It is released during the 17th workday of each month.[16] Housing starts is released by the Census Bureau. It measures the number of housing projects started in the previous month. It is

[14] More information about the Employment Report and Employees on Non-Farm Payrolls can be found at http://www.bls.gov/ces/

[15] For further information about the Trade Balance, visit http://www.bea.gov/international/

[16] More information about New Home Sales can be found at http://www.census.gov/construction/nrs/

released during the 10th workday of each month.[17] The housing market plays an important role in the economy and housing booms have been shown, Cecchetti (2008), to predict economic growth trends.

Industrial Production

Industrial Production is released in the G.17 report by the Federal Reserve Board. It is a measure of real output that is estimated using information from the manufacturing-, mining-, gas- and utilities industries.[18]

Federal Funds Rate

Decisions on the Federal Funds Rate are taken during FOMC meetings. Each year have 8 scheduled meetings, but unscheduled meetings can take place as a response to economic conditions. The scheduled meetings takes place; in January/the beginning of February, at the end of March, at the end of May, at the end of June/in the beginning of July, in the middle of August, at the end of September, in the middle of November and one before Christmas. Pre 1994, FOMCs decision of the targeted Federal Funds Rate was generally released the day after the last meeting day. However, the exact time of release varied and in some instances it was released on the day of the meeting as well. Starting with the March meeting in 1994 and onwards the rate decision has been released at 2:15 PM of the last day of their meetings. To facilitate the measuring of the surprise component of the decision and the stock return reaction, only scheduled releases from March 1994 will be used.[19]

1.3.1.3 Explanatory variables – Firm characteristics

Acid Ratio

The Acid ratio is often used as proxy for firms' balance sheet liquidity. A high value indicates that the firm in question is very liquid and should be able to handle unexpected shocks to their cash flow well. Hence a low value indicates that the firms' balance sheet is illiquid and could have problems financing day to day operations.

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[17] For more information about Housing Starts, visit http://www.census.gov/construction/nrc/

[18] More information about the G.17. report and Industrial Production can be found at http://www.federalreserve.gov/releases/G17/About.htm .

[19] For more information about the FOMC, their meetings and reports please visit http://www.federalreserve.gov/monetarypolicy/fomc.htm

$$Acid\ Ratio = \frac{Current\ Assets - Inventories}{Current\ Liabilities}$$

Debt to Equity-ratio

The debt to equity-ratio measure the amount of leverage a firm has. In which way they have financed their assets. A high value means that a high portion of the firms' liabilities are in the form of debt. When firms incur losses these are booked against the firm's equity, which serves as a cushion for debt-holders. If the ratio is high, small value changes to a firm's asset are amplified for equities.

$$Debt\ to\ equity\ Ratio = \frac{Total\ Debt}{Total\ Equity}$$

Book to Market

The book-to-market ratio measures the difference between accounting value of equity and market value of equity. Firms with high values are often labeled value firms while firms with low values are considered growth firms. Cenesizoglu (2011) found different responses of book-to-market sorted portfolios to macroeconomic announcements.

$$Book\ to\ Market\ Ratio = \frac{Book\ Value\ of\ Equity}{Market\ Value\ of\ Equity}$$

Size

This variable measures the size of the company in terms of its market value. Not only have size been found to be a prized risk-factor (Fama and French, 1993), Adams, McQueen and Wood (2003) found that size sorted portfolios responded differently to macroeconomic announcements.

$$Size - proxy = \log(Market\ Value)$$

Illiquidity

Market illiquidity has been found, Gilbert (2011), to play an important role in explaining stock responses to firm-specific news. This could also be true for macroeconomic news. The variable Illiq, defined by Amihud (2002), is used to capture the illiquidity of stocks. The variable is calculated on a daily basis and then averaged over one year. A low value means that the stock is liquid while a high value suggests it is illiquid. For day *t* the variable is calculated as follows:[20]

$$Illiq_t = 1000 * \frac{|return_t|}{Volume_t * Price_t}$$

Labor Intensity

Ideally Labor intensity would be an explanatory variable in the second step regression. Reliable data on Employee Compensation cannot however be found without large implication for the sample size and it is therefore omitted even though Gilbert et at. (2011) found the degree of Labor Intensity to have a relationship with Employees on Non-Farm Payrolls announcements.

1.3.2 Unexpected announcements

According to the Efficient Market Hypothesis (EMH), derived independently by Fama (1965) and Samuelson (1965), the stock price always incorporates all public available information. Hence an announcement in itself should not cause market moves, only the deviations of an announcement from the market's expectation. To be able to estimate the importance of different macroeconomic news for stock prices, it is crucial to get an efficient estimate of the unexpected part of an announcement.

When it comes to macroeconomic announcements one also has to assume that all public information is not easily and freely available to every investor. Since most indicators released by various agencies are in themselves summaries of public information, it can be argued that the information they convey should already be incorporated in all asset prices. The information is however not easily obtained which makes us able to treat the reported values as private, or unknown public, information before they are released. The observed difference between forecasts and the released values is a good example to why this assumption holds, even though there could be that some investors have access to more information than others (see for example Bagnoli, Benesih and Watts, 1999, on a discussion about "Whisper-forecasts" that only are available to informed investors and Viale, 2009, for a more lengthy discussion if macroeconomic announcements are ambiguous events).

[20] Days with zero volume or no return are set to 0.5.

There are a number of problems that have to be solved to reach efficient estimates. As detailed above in II.A a number of different methods have been used recently. The consensus method within the literature has been to use forecasts reported by MMS or Bloomberg (see the empirical framework in for example Cenesizoglu, 2011). Some studies have modeled the expected component of macroeconomic data, mainly to be able to extend the time-period. This is done with both older observations when survey values were not present and with new observations due to dataset limitations, and not because it is superior to survey forecasts.[21]

I have chosen survey estimates since the time-period of my available dataset meets my needs and mainly because it has been shown in prior studies to produce less biased estimates than modeling approaches (Balduzzi et al. 2001). Although this method has certain strengths it also has some weaknesses. As Rigobon and Sack (2008) argues, even if one is able to measure the markets expectation, the reported value itself could be viewed as a noisy estimate of the actual information that in fact affects asset prices (evidence found in Gilbert, 2011, do also point in this direction). Another problem is that many of the indicators used are only a component of a larger report, even if it is the most important component, and it is likely that the value of the indicator is caused by different factors that may be going in different directions, making it even more difficult to deduct the causal relationship between macroeconomic surprises and asset prices.[22]

The most important component is how well surveys measure the beliefs of the market. The survey responses are often treated as market consensus in a number of different forums. This does not however have to be true. The respondents in these surveys are most commonly analysts and not traders. Although the views of these two different groups align in some cases they do not have to have the same view. Since the actual trades are carried out by traders and not analysts, the views of traders should be the focus. This data is not available through surveys and cannot be extracted from the most popular traded assets. This discrepancy could pose a problem for an efficient estimate of the market's expectations. Recent studies do however strengthen the argument for treating the analysts' responses to surveys, as MMS and Bloomberg, as a proxy for the market view (see finding of Lanne, 2007, that survey's forecasts do not show any considerable deviations from forecasts extracted from derivatives). Rigobon and Sack (2008) propose to measure the impact on returns

[21] See Rigobon and Sack, 2008, for an overview of the evolution of the empirical framework when estimating the effects macroeconomic announcements have on asset returns.
[22] Consumer Confidence is, for example, a weighted average of the "Present Situation Index" and "The Expectations Index".

through IC-approach. They are able to get significant results with this approach, and especially higher coefficients. They do however argue that their findings are likely to be biased since their estimates of noise contained in news releases often are too high to be plausible. Their IC approach does for example measure the noise in the measured surprise component for ISM to be above 94 percent. Given the limitations of the IC framework and its reliance on intra-day data I choose to use the Event-Study approach that most papers in the field have used (see McQueen and Roley, 1993, as well as Cenesizoglu, 2011, for two good examples). In all regression specifications in Chapter III. Section B., the independent variable will be the unexpected announcement of the specific macroeconomic data release. Table 1 presents the "data format" of each release. The general procedure follows below.

$$z_{it} = \phi z_{it}^{*} + \omega_{it} \tag{2}$$

In equation 2. z_{it} is defined as the estimated unexpected component of the release value, and z_{it}^{*} is the true unexpected component and omega is an error term. With the problems of deriving a model that are robust to outlier values of its variables, most studies, as previously discussed, have used various analyst estimates of the expected value as the market expectations and then defined the unexpected part as below:

$$z_{it} = Announcement_{it} - Forecast_{it} \tag{3}$$

When aggregating the different announcements and using the dataset for all announcements I follow the procedure in Balduzzi et al. (2001) and Andersen et al. (2003) and divide the surprise component of the data release with the standard deviation of the surprise components for that specific variable. This will transform all different announcements so they are of the same magnitude and can be used in an aggregated "macroeconomic news release" dataset and in a multiple regression. The full dataset starts in 1990, with the exception of FF that starts in March 1994. Consumer confidence, ISM and GDP have their very first observation in 1990, so for 1990, the standard deviation for these variables is calculated using the help of future observation that is not known at the time of announcement. For all the other variables and beyond 1990 for Consumer Confidence, ISM and GDP only information known at the time of the release is used:

$$z_{it}^{std} = \frac{Announcement_{it} - Prediction_{it}}{\sigma_{z_{it}} | \mathcal{F}_t} \quad (4)$$

The surprise component of the announcement after the FOMC meeting is different from the other macroeconomic factors and is defined as the change of the price of the Federal Funds Futures 1 month contract from day *t=-1* to day *t=0* and adjusted for the number of days left before the settlement of the contract. This method follows Bernanke and Kuttner (2005) and is defined as follows:

$$\Delta i^u = \frac{D}{D-d}\left(f_{m,d}^0 - f_{m,d-1}^0\right) \quad (5)$$

In equation 5. Δi^u equals the unexpected news value, *D* is defined as number of calendar days in the month, *d* is the number of calendar days left in the month, $f_{m,d}^0$ is the implicit interest rate for a Fed Fund Futures at the end of the trading day when the FOMC meeting is conducted and $f_{m,d-1}^0$ is the implicit interest rate from the preceding day's Federal Funds Futures price.[23]

1.3.3 Beta Estimation

To estimate the effect on stock returns of macroeconomic news I will regress the daily return of a set of stocks on the unexpected component of a news release, z_{it}. To get a thorough understanding of what effect macroeconomic news have on equity returns a number of different specifications will be used. The standard procedure is defined as:

$$r_{ij} = \theta_{ik} + \beta_{ik} * z_{kj} + \varepsilon_{ij} \quad , \forall\, i \;\&\, k \quad (6)$$

In the regression equation 6. , *i* denotes firms, *j* the date of announcement, *k* the announcement, r_{ij} is the daily return, θ the intercept and ε the error term. In this setting, state-dependent effects or asymmetric effects will not be detected. The betas can only incorporate reactions to the direction of the unexpected news and its magnitude. A second specification will be an alteration of the standard procedure, but in place of the individual announcements I will instead use the standardized announcements from equation (4) in an aggregate dataset. With this specification the betas will be interpreted as the reaction to macroeconomic announcements in general. To avoid betas converging to zero because of the different definitions of good and bad news relative to positive and negative

[23] The value of a Federal Funds Future at expiration is 100 minus the current Federal Funds Rate in percentages:
FFF = 100 – (Federal Funds Rate * 100)

unexpected announcements, the announcements that have an average beta less than zero from equation 6. are multiplied with minus unity.[24]

$$r_{ij} = \theta_i + \beta_i * z_j^{std} + \varepsilon_{ij} \quad , \forall\, i \tag{7}$$

As a compliment to the specifications 6. and 7. above, an additional multiple regression will be used where each of the standardized announcements are used as explanatory variables:

$$r_{ij} = \theta_i + \beta_{ik} * Z^{std} + \varepsilon_{ij} \tag{8}$$

Regression 8. will also be performed with the market index as an explanatory variable. This alteration will control for the impact from the market and the betas will instead of showing the response to the announcement display how stocks react differently compared to the market index. This specification does also allow me to include more observation from the same trading day, e.g. the unemployment rate and Employees on Non-Farm Payrolls can be used together.

To increase the likelihood of efficient beta estimations, each stock will have to have at least 60 observations (for specification 6. and 7.), which is equal to 5 years of observations for the variables that are reported at a monthly frequency. For specification 8., the stocks with less than 650 observations will be filtered out (this is equal to 5 full years of observations). This is done so that stocks with, for example, only five observable returns in connection with macroeconomic announcement are not used. Hence each sample of estimated betas will include betas estimated during different time periods, i.e. some betas in the sample would be connected to stocks only present at the beginning of the time window, others would be connected to stocks that are only present at the end and some would belong to stocks that were traded throughout the whole period. This creates two major problems when interpreting the results. The first is that it opens up for time-period bias which could be aggravated if the responses were to be state-dependent. In other words, if my sample of estimated betas contains a large number of betas that are estimated using only returns from the last 5 years, the reaction to macroeconomic news during these 5 years would have an abnormally large weight when examining average betas. Hence one could reach conclusions about the results from the full-period which only are true for one of the sub-periods.

[24] The variables with an average negative beta are Inflation, Federal Funds Rate, Employees on Non-Farm Payrolls and Industrial Production.

Prior research have found contradicting results but with an indication of that responses are state dependent (see for example Poitras,2004 for results indicating that state dependence are not present and McQueen & Roley, 1993 or Cenesizoglu, 2011 for results that show that responses are state dependent). The other problem that could appear with this restriction occurs if the true betas are time-varying. The evidence for time-varying market betas have been well documented (see for example Jagannathan & Wang, 1996 or Harvey, 1991). As both firm-characteristics and market-betas are time-varying over time-periods much shorter than 22 years this could also be true in this setting for announcement betas. In other words, a certain stock may react to macroeconomic announcements in one way during the early 1990s, while it reacts to macroeconomic announcements in a different way during the late 2000s. This could be true if the stock in question, for example, has changed its business or has grown from a small-cap stock to a large-cap stock. To guard against these potential biases the results will also be presented for 4 different sub-periods. An extension will also be used to allow for state dependent effects:

$$r_{ij} = \theta_{ik} + \beta_{ik}^{e} * z_{kj} * D_j^{e} + \beta_{ik}^{c} * z_{kj} * D_j^{c} + \varepsilon_{ij} \quad , \forall\ i\ \&\ k \qquad (9)$$

In regression equation 9. , D_j^e is a dummy-variable that takes the value of 1 in expansions and zero otherwise, likewise D_j^c takes a value of 1 when the announcement occurs in a contraction and 0 otherwise. Hence the specification allows for state-dependent effects as well as those of magnitude and direction as in specification (6). The definitions of expansions and contractions follow NBER and are hence determined ex-post the release. The contraction periods from NBER's definition are: July 1990-March 1991, March 2001-November 2001 and December 2007-June 2009. An alternative definition of recessions will also be used as a robustness test. The contraction periods are estimated with the help of a simple, univariate Markov Switching Model for Industrial Production Growth. The Markov Switching Process whose parameters are driven by a state variable (expansion or contraction) follows:

$$y_t = \mu_{s_t} + \sum_{j=1}^{p} a_{j,s_t} y_{t-j} + \sigma_{s_t} u_t, \ \ u_t \sim IIN(0,1) \qquad (10)$$

State-Transitions are governed by a constant transition probability matrix:

$$P(S_t = s_t | S_{t-1} = s_{t-1}) = p_{s_t s_{t-1}}, \qquad s_t, s_{t-1} = 1,2 \qquad (11)$$

The parameters are estimated using Maximum Likelihood. Using the estimates for the probability of a state-transition, I define months with a probability estimate above 0.5 as a contraction month.[25] The parameters are estimated using only information available at the time and it is hence, unlike NBER's definition, forward-looking. With this definition the contraction periods are: September 2005 and September 2008-June 2009.

With a limited number of recession observations this method (equation 9) will only be used with the full time-period. The equations 6, 7, 8 and 9 will also be estimated with the value-weighted return of all NYSE, NASDAQ and AMEX stocks as the dependent variable instead of individual stocks. When the market is used as the dependent variable, the problem with eventual state-dependence is still present for the first regression specification (equation 6.), time-varying betas should however not be a problem to the same extent since firms obviously change characteristics with much higher frequency than the market. It should take longer for the market to change the way it reacts to macroeconomic announcements than for individual stocks, therefore time-varying announcements betas should not be an issue to the same extent with the market as the dependent variable.

As mentioned above r_{ij} is the daily return. In an ideal setting with unlimited data availability the measured return would be intraday and limited to a short period of time directly after the macroeconomic announcement to limit noise from idiosyncratic news occurring during the day as well as other economic and financial news. Intraday returns are however not available to me why daily returns are used instead. To limit the problem this creates, the above mentioned restriction of only including stocks that have at least 60 return observations that coincides with macroeconomic announcements is imposed. Hence the assumption is that these idiosyncrasies and other information that carries financial value for the stock in question will average out. This is a rather strict assumption with only 60 observations, evidence in earlier literature does however point to that the assumption holds up reasonably well for the market index (see the comparison of results when using daily vs. 25-minute returns in Rigobon and Sack, 2008) and the shorter examined period return does not alter the results in a significant fashion. The higher return volatility of individual stocks makes this parallel a bit ambiguous for each individual stock, the results are however aggregated across all stocks and if idiosyncratic news does not average out for each individual stock there is a high chance that this effect is either averaged out or mitigated in the aggregate.

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[25] Please refer to Guidolin and Timmermann, 2006, Section 2.2 for a more comprehensive review of the Markov Switching Model used.

The full time-period is 1990-2011. The four sub-periods for the announcements that are reported monthly are 1990-1995, 1996-2000, 2001-2005 and 2006-2011. For GDP two sub-periods are used: 1990-2000 and 2001-2011. Since the Federal Funds Rate dataset starts later their two sub-periods are 1994(March)- 2002 and 2003-2011.

During these estimations three different t-statistics are used for verification of the statistical significance of the betas and the differences between them. First the average of the student's t-statistic is used.[26]

$$t_1 = \frac{\sum \frac{\beta_i}{s_i/\sqrt{n_i - 1}}}{n} \tag{12}$$

As a second method the estimated betas are treated as a sample and the t-stat calculated as:

$$t_2 = \frac{\bar{\beta}}{\frac{s_\beta}{\sqrt{n_\beta - 1}}} \tag{13}$$

To detect any differences between the responses during expansions against contractions as well as different returns between portfolios (see Section E), Welch's t-test is also used (Welch, 1947). This correction of the standard student's t-test is used when two samples are compared and the compared samples cannot be assumed to have equal variance while the number of observations is small. Since I cannot assume that the sample of contractions betas has the same variance as the sample of expansions betas, Welch's t-test is used in favor of (13). With the same line of thought, the portfolios constructed sorting with respect on announcement betas could have certain characteristics that make their return more or less volatile why (14) is used for that specification as well.

$$t_3 = \frac{\overline{\beta^e} - \overline{\beta^c}}{\sqrt{\frac{s_{\beta^e}^2}{n_\beta - 1} + \frac{s_{\beta^c}^2}{n_\beta - 1}}} \tag{14}$$

All of the above statistics assumes that the betas approximately follow a t-distribution. The statistical method was developed when the distribution of sample means could not be assumed to follow a normal distribution.

[26] See for example Newbold et al. (2007), p. 301

1.3.4 Second-step Regressions

Given the results from the empirical specifications in Chapter III. Section A., the betas will be analyzed in two different ways. First, since the regressions are run on an individual stock level, I will use a number of firm-specific variables to examine what causes the announcement betas to be different across stocks:

$$\beta_i = \alpha_i + \gamma_i \boldsymbol{X}_i + \phi_i Y_i + \omega_i \tag{15}$$

In this regression specification (equation 15.) the matrix **X** consists of firm-specific variables that could explain the different responses in III.A. Matrix **Y** consists of year-dummies with the first year, 1995, omitted and included in the intercept. The ratios: Acid, Book-to-Market, and Debt-to-Equity will be used together with the log of Market Value and *Illiq* as the firm-specific measures for each sub-period (for more information on these variables please see III.A.iii). β_i will be defined as the estimated betas from regression (6), without allowing for state-dependence. To get explanatory variables that describe each firm's characteristics as good as possible the betas are estimated using rolling 5-year periods starting in 1991-1995 and ending with 2007-2011. The firm-characteristic variables are defined as the values in the final year of the estimation period. With this procedure I get a larger sample than if I was to use only the full time-period. When using sub-period betas I can use 17 different betas instead of one for all the stocks that were traded throughout the sample. Instead of having to calculate explanatory variables as averages over a long period of time, as for example 22 years which would be the case for some stocks, I define the macroeconomic announcement beta as the one estimated at time t (1995,1996…,2011). This definition also allows me to analyze and control for differences in reactions that are due to different states of the economy or time-periods used. Regression (6) is estimated using a number of different independent variables and all of those that are reported on a monthly basis will be used in (9).

1.3.5 Sorting Procedure

A further extension of the first set of results will be to sort the stocks into deciles with respect to their announcement beta, from regression (6), and look for a spread from high to low to see if the sensitivity to macroeconomic news could be a proxy for some unspecified systematic economic risk factor. The intuition behind sorting with respect to the sensitivity of the macroeconomic environment has it theoretical background in ICAPM (Merton, 1973). Stocks that perform badly in a bear market and amplify rather than hedge a dismal overall market performance should command a risk premium. Hence, they should perform as badly (or worse) as the market in downturns and make up for this with a better than average performance in good times. If this is the case, bad news should indicate especially bad times for stocks that are highly correlated with the market in bear times and good news should generate a higher response than stocks that have a lower downside-beta.

Stocks will be sorted according to both their aggregate announcement beta, from high positive beta to high negative beta and their beta for ten individual announcements. To get estimates that characterize the current sensitivity to macroeconomic announcement as much as possible, the original regressions (equation 6.) will be performed in rolling five year periods from the period 1990-1994 up until 2007-2011. With this rolling procedure, I will get a higher number of portfolio returns and this higher number of observations should enable me to get a better estimate of how different announcement betas translate into stock returns. If I only used the sorting procedure after each of the four sub-periods from the first step-regression, I would end up with 4 different contemporaneous returns for each portfolio and 3 different out-of-sample return for each portfolio. With such a low number of observations, an outlier within the sample could lead me to draw the wrong conclusions. With the rolling procedure I will instead get 18 contemporaneous returns and if a portfolio, by pure chance, have an abnormally high return for one of these periods its impact on the final result would be much lower than in the case of only 4 observations. For each of these 18 regression periods the stocks are sorted according to their betas and placed into 10 different portfolios depending on in which decile they are after sorting. Hence I will end up with 10 different portfolios where there is dispersion in announcement betas from high to low across the portfolios but with homogenous announcement betas within each of the portfolios. After placing the stocks into portfolios, both the contemporaneous return, defined as during the whole 5-year period, and the 5-year out of sample return for each portfolio will be calculated. Subsequently the equally-weighted and value-weighted returns within each decile are then averaged over the 18 time-periods and the spread from high to low will be compared. If I can find a return spread from high to low, this would indicate that the stocks with high announcement beta (or low if the reversed is true that the lowest decile portfolio has a higher mean return) are exposed to some risk factor which results in them experiencing a higher return. The comparison of returns will be made for both the tenth decile (the portfolio with highest announcement beta) minus the first decile (the portfolio with lowest announcement beta) and the average of the three highest deciles minus the average of the three lowest deciles. Ideally a spread from high to low should also be accompanied by a monotonic pattern between the first and tenth deciles. If the announcement betas are strongly correlated with some known risk-factor, it would create a possibility of not only getting dispersion of macroeconomic announcement betas across the deciles but also dispersion in that specific risk-factor. If the results indicate this, a double sorting procedure will be added as a robustness check. For example, if the result of the sorting procedure appears to be explained by the correlation between announcement betas and the size of firms, stocks will be sorted with respect to their size and then within each decile the stocks will be sorted with respect to their macroeconomic betas. The spread from high to low are then analyzed within each size decile. This procedure will generate homogenous firm size and beta dispersion within each size decile, hence if a significant spread is detected size has been controlled for and it is likely that it is the macroeconomic announcement betas that causes the spread.

1.4 Results

In Chapter IV the results from the empirical exercises are presented. The Chapter is divided into three Sections: Section A. presents the results from the first step regressions where the announcement betas are estimated. Section B. handles the results from the second-step regressions where I try to explain the estimated betas from Section A. Section C. and the results from the sorting procedure conclude the Chapter.

1.4.1 First step Regressions

In the basic framework when the return of each individual stock is regressed on the surprise component of macroeconomic announcements, none of the announcements yields a significant stock reaction on average, neither for the full time-period nor the sub-periods. There is however some announcements that seems to carry valuable information for a high portion of the stocks in the sample. In Table 2, an overview of the results is presented. The announcement that has the highest portion of significant responses is Retail Sales with roughly 20 percent of the stocks having a significant response at a 5 percentage level. For Trade Balance, Industrial Production and Non-Farm Payrolls approximately 10 percent of the stocks are significant at a 5 percentage level. We can also observe, by looking at both the number of positive betas and the percentage of significant betas being positive, that only five announcements give a clear indication in which direction returns will

Table 2

Table 2 presents a summary of the results for the first regression (equation 6.), when each individual stock return is used as the dependent variable. The table presents; number of firms included in the regression, the number of these firms that have a positive beta, the number of total firms with an estimated beta significant at the 5% level, the percentage of the significant betas that are positive,the percentage of firms that react to at least one of the announcements and the percentage of all betas that are significant at the 5% level.

	Inflation	**Trade Balance**	**Retail Sales**	**Non-Farm Payroll**	**ISM**	**IP**
Number of firms	10371	10498	10541	10284	10464	10506
No. of firms with positve β	3652	7069	6754	4638	5672	4090
No. of firms with significant beta	577	849	2161	996	661	1145
Portion of significant betas being positive	16%	85%	89%	29%	43%	20%
	Housing Starts	**Home Sales**	**GDP**	**CC**	**Federal Fund Rate**	
Number of firms	10513	10444	2822	9940	6323	
No. of firms with positve β	5324	5169	1437	5043	2647	
No. of firms with significant beta	439	336	140	709	380	
Portion of significant betas being positive	44%	47%	60%	52%	38%	
Percentage of firms with at least 1 significant beta						
55,26%						
Percentage of betas that are significant at the 5% level						
8,17%						

move. Trade Balance and Retail Sales have a high number of positive betas and an even higher portion of the significant betas being positive. The interpretation is that, if the unexpected component of an announcement is above the forecast, stock prices tend to increase. In the other direction Inflation, Non-Farm Payrolls and Industrial Production have a high number of negative betas and an even higher percentage of the significant ones being negative. All of these signs except for Industrial Production are the expected ones. We would expect a higher Trade Balance and Retail Sales to be solid indicators of an expanding and well- functioning economy which generates hope of a beneficial trajectory of future profits.

Higher Inflation both indicates some costs for firms in general, but do also give a hint of future Federal Funds Rates being higher which would increase the cost of capital of firms, hence increasing the discount factor and resulting in lower prices. As for Non-Farm Payrolls, it should both be thought of as a good indicator of the employment situation in the country but it is also an important

<table>
<tr><th colspan="11">Table 3</th></tr>
<tr><td colspan="11">Table 3 displays the results from regression 6. for Advanced GDP, Industrial Production and the Federal Fund Rate as well as regression 7. with the aggregate dataset as the explanatory variable. The average intercept for each stock is presented along with its t-stat. The average beta and its the average t-stat (equation 12.) is presented on the same row and the t-stat for the average beta (equation 13.) on the row below. Coefficients significant at the 5 percentage level are marked bold.</td></tr>
<tr><td></td><td colspan="2">Full Period</td><td colspan="2">1990-1995</td><td colspan="2">1996-2000</td><td colspan="2">2001-2005</td><td colspan="2">2006-2011</td></tr>
<tr><td>Merged</td><td>Coef</td><td>t</td><td>Coef</td><td>t</td><td>Coef</td><td>t</td><td>Coef</td><td>t</td><td>Coef</td><td>t</td></tr>
<tr><td>Intercept</td><td>0,001</td><td>1,071</td><td>0,001</td><td>0,836</td><td>0,002</td><td>1,019</td><td>0,001</td><td>0,879</td><td>0,001</td><td>0,986</td></tr>
<tr><td>Avg β</td><td>0,000</td><td>0,937</td><td>0,000</td><td>0,776</td><td>0,001</td><td>0,846</td><td>0,000</td><td>0,742</td><td>0,001</td><td>1,117</td></tr>
<tr><td></td><td></td><td>13,358</td><td></td><td>2,198</td><td></td><td>9,385</td><td></td><td>1,688</td><td></td><td>28,030</td></tr>
<tr><td></td><td colspan="2">Full Period</td><td colspan="4">1990-2000</td><td colspan="4">2001-2011</td></tr>
<tr><td>GDP</td><td>Coef</td><td>t</td><td colspan="2">Coef</td><td colspan="2">t</td><td colspan="2">Coef</td><td colspan="2">t</td></tr>
<tr><td>Intercept</td><td>0,002</td><td>0,894</td><td colspan="2">0,002</td><td colspan="2">0,289</td><td colspan="2">0,002</td><td colspan="2">0,396</td></tr>
<tr><td>Avg β</td><td>0,000</td><td>0,783</td><td colspan="2">0,000</td><td colspan="2">-0,016</td><td colspan="2">0,001</td><td colspan="2">0,078</td></tr>
<tr><td></td><td></td><td>2,118</td><td colspan="2"></td><td colspan="2">-1,345</td><td colspan="2"></td><td colspan="2">6,329</td></tr>
<tr><td></td><td colspan="2">Full Period</td><td colspan="2">1990-1995</td><td colspan="2">1996-2000</td><td colspan="2">2001-2005</td><td colspan="2">2006-2011</td></tr>
<tr><td>IP</td><td>Coef</td><td>t</td><td>Coef</td><td>t</td><td>Coef</td><td>t</td><td>Coef</td><td>t</td><td>Coef</td><td>t</td></tr>
<tr><td>Intercept</td><td>0,001</td><td>1,071</td><td>0,001</td><td>0,201</td><td>0,000</td><td>0,138</td><td>0,001</td><td>0,293</td><td>-0,001</td><td>-0,375</td></tr>
<tr><td>Avg β</td><td>0,000</td><td>0,937</td><td>0,000</td><td>0,032</td><td>-0,002</td><td>-0,202</td><td>0,002</td><td>0,160</td><td>-0,006</td><td>-0,790</td></tr>
<tr><td></td><td></td><td>1,000</td><td></td><td>-0,077</td><td></td><td>-5,786</td><td></td><td>9,715</td><td></td><td>-30,670</td></tr>
<tr><td></td><td colspan="2">Full Period</td><td colspan="4">1994-2002</td><td colspan="4">2003-2011</td></tr>
<tr><td>FF</td><td>Coef</td><td>t</td><td colspan="2">Coef</td><td colspan="2">t</td><td colspan="2">Coef</td><td colspan="2">t</td></tr>
<tr><td>Intercept</td><td>0,003</td><td>1,279</td><td colspan="2">0,001</td><td colspan="2">0,324</td><td colspan="2">0,005</td><td colspan="2">1,068</td></tr>
<tr><td>Avg β</td><td>-0,005</td><td>0,799</td><td colspan="2">-0,001</td><td colspan="2">-0,059</td><td colspan="2">-0,007</td><td colspan="2">-0,128</td></tr>
<tr><td></td><td></td><td>-9,303</td><td colspan="2"></td><td colspan="2">-0,688</td><td colspan="2"></td><td colspan="2">-7,925</td></tr>
</table>

indicator of the level of inflation. Given the results summarized in Table 2, it seems that information for inflation dominates the information of the positive consequences of high employment for the economy or the more likely case that inflation is far more important for stocks in general than the employment figures. The result for Industrial Production is a bit puzzling. Industrial Production figures plays an important role when FOMC determines the outlook for the economy, hence positive Industrial Production figures could be an indication of a more strict monetary policy which is why the response is negative. Industrial Production Growth is for example used in my robustness definition for contraction dates and in general it is also an important variable for determining current states of the economy. For the other five announcements; ISM, Housing Starts, New Home Sales, advanced GDP, FOMC decisions and Consumer Confidence, there are no clear indications of the direction of the stock response. The findings of state dependence could however impact the results in this setting when the full time-period is used.

In this framework when using the individual stock returns instead of broad indices we can also examine how the same stock reacts to different announcements. Some firms could be very dependent on some announcements while others do not matter much. We can note that this seems to be the case. 55.26 percent of the stocks have a significant estimated beta for at least one of the announcements. The underlying fundamentals for this will be more closely examined in the second-step regressions (Chapter IV. Section B).

With the dataset consisting of every traded stock in US markets, a considerable amount of stocks were illiquid stocks without any price movements for some parts of the sample, which could mean that measured movements were extremely noisy and incorporated information during earlier days or

Table 4

Table 4 presents the results when the returns of each individual stock are regressed on unexpected component of macroeconomic announcements (equation 6.). The results are for all macroeconomic announements that are released with a monthly frequency. The coeffients presented are the averages from all regressions. Two different t-statistics are presented: the t-statistic on the same row as the coefficient is the average t-statistic (equation 12.) while the t-statistic on the row below is the t-statistic of average coefficients (equation 13.). The first column presents the results from the full time-period, the second through fifth column presents the results from the sub-periods. Coefficients significant at the 5 percentage level are marked bold.

	Full Period		**1990-1995**		**1996-2000**		**2001-2005**		**2006-2011**	
Inflation	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Avg Intercept	0,001	0,861	0,002	0,292	0,003	0,519	0,001	0,092	-0,001	-0,372
Avg β	-0,003	-0,802	-0,004	-0,322	-0,004	-0,259	-0,004	-0,403	-0,002	-0,162
		-17,742		**-12,187**		**-9,425**		**-17,955**		**-9,651**
Trade Balance	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Avg Intercept	0,001	0,873	0,000	-0,070	0,002	0,272	-0,002	-0,556	0,002	0,422
Avg β	0,001	0,905	0,000	0,099	0,001	0,226	0,000	0,300	0,001	0,549
		21,524		**6,477**		**13,423**		**19,271**		**36,433**
Retail Sales	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Avg Intercept	0,001	0,913	0,002	0,431	0,002	0,270	0,001	0,056	0,000	-0,146
Avg β	0,002	1,194	-0,001	-0,170	-0,003	-0,152	0,000	-0,035	0,011	**1,715**
		18,331		**-5,426**		**-9,154**		**-3,103**		**72,545**
Non-Farm Payroll	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Avg Intercept	0,001	0,835	0,001	0,080	0,005	0,875	0,000	-0,128	0,000	-0,008
Avg β	0,000	-0,928	0,000	0,141	0,000	-0,960	0,000	0,098	0,000	0,417
		-4,186		**7,208**		**-45,762**		**14,477**		**23,248**
ISM	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Avg Intercept	0,001	1,075	0,001	0,243	0,003	0,664	0,002	0,644	0,000	0,095
Avg β	0,000	0,850	0,000	-0,021	-0,001	-0,348	0,000	0,190	0,001	0,429
		4,826		-1,113		**-15,689**		**14,453**		**27,227**
Housing Starts	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Avg Intercept	0,001	0,796	0,000	-0,050	0,003	0,437	0,000	0,081	0,000	0,170
Avg β	-0,002	-0,758	0,006	0,109	-0,030	-0,321	-0,005	-0,071	0,021	0,382
		-3,605		**4,590**		**-21,917**		**-7,770**		**26,364**
New Home Sales	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Avg Intercept	0,002	1,094	0,002	0,568	0,001	0,239	0,002	0,581	0,004	1,111
Avg β	0,000	0,696	0,000	-0,065	0,000	0,055	0,000	-0,204	0,000	0,226
		3,210		-0,734		**6,030**		**-11,938**		**20,453**
Consumer Confidence	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Avg Intercept	0,002	1,034	0,001	0,324	0,002	0,482	0,002	0,451	0,003	0,774
Avg β	0,000	0,870	0,000	-0,102	0,000	0,043	0,000	0,501	0,000	-0,417
		7,187		-0,496		**5,855**		**24,107**		**-16,812**

that the reactions showed up in the returns after the announcement day due to lack of market depth. Therefore the same procedure was also performed using a filter that deleted the illiquid stocks present in the sample that did not have any stock price movement 25 percent of the time of announcements. The results for the filtered dataset showed a lower portion of significant betas, suggesting that also the illiquid stocks do react to announcements moves and even with a higher frequency than both a dataset only containing liquid stocks and hence also the full dataset.[27]

When looking at the average t-stats across stocks for each announcement, none are close to being significant at a 10 percentage level, the results for GDP, Federal Funds Rate and the aggregate dataset can be seen in Table 3 and the monthly announcements can be observed in Table 4. Retail Sales is the only announcement with an average t-stat above 1 for the full time-period. It is also the only announcement that has an average beta significant at the 10 percent level for one of its sub-periods with a t-stat of 1.715 during the sub-period 2006-2011. With a coefficient of 0.2 percent for the full time-period, this translates into a 0.2 percent return for each unexpected percentage point in the reported value. For the significant sub-period the same coefficient is 1.1 percent. In other words an unexpected Retail Sales growth of 1 percentage point would yield a 1.1 percent increase in the

Table 5

Table 5 displays the results from regression (6) when thethe two announcements that are not reported monthly (GDP and FF) are regressed on the value weighted return for all traded US stocks and the results from regression (7) when the aggregated standardized announcements are used as the explanatory variable. Coefficients significant at the 5 percentage level are marked bold.

	Full Period		**1990-1995**		**1996-2000**		**2001-2005**		**2006-2011**	
Aggregate	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,001	**3,413**	0,000	1,431	0,002	3,429	0,000	0,214	0,001	1,799
beta	0,001	**2,577**	0,000	0,081	0,001	1,450	0,000	0,751	0,002	**2,251**

	Full Period		**1990-2000**		**2001-2011**	
GDP	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,001	0,498	0,001	0,550	0,000	0,237
beta	0,000	0,254	0,000	-0,036	0,001	0,309
	Full Period		**1994-2002**		**2003-2011**	
FF	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,003	**3,298**	0,002	**2,215**	0,004	**2,502**
beta	0,001	0,083	0,004	0,449	-0,009	-0,391

[27] Note that the reaction could be more significant if the announcement days returns also are caused by earlier event that alone could not trigger a price movement.

average stock price, or a 1.1 percent increase in an equally weighted index of the full market. An average increase of 1.1 percent is also an economically significant reaction since we observe that the mean unexpected value for Retail Sales is -0.3 with a standard deviation of 0.4. None of the other announcements produces reactions that are in the neighborhood of being economically significant.

If we instead look at the significance levels when we treat our estimated betas as a sample instead of looking at the average t-stats the results are vastly different. Using this way to measure the t-statistics (equation 14.), all announcements, except Industrial Production, have a significant effect on the stock returns for the full time-period. The aggregate dataset, Inflation, Retail Sales and Trade Balance are the announcements that have the most significant estimates of betas. Trade Balance and Inflation show monotonic results across the different sub-periods which points to that these variables are less state-dependent than Retail Sales that actually have a negative response in the first three sub-periods along with their, as mentioned above, highly significant and positive coefficient for the last sub-period. Non-farm Payrolls has a negative beta for the full time-period but a positive beta for three of the sub-periods. Since Non-Farm Payrolls can give information both regarding the employment situation and the inflation level, as discussed above, varying importance for inflation and employment could be a factor in the sign-switching for Non-Farm Payrolls. The results are in the same direction in the multiple regression (equation 9.), which suggests that the estimated betas with this specification are not affected by information coming from the simultaneously released Unemployment Rate (see Table A. in the Appendix).

If we compare the results across sub-periods they are considerably different. In the chaotic market environment that plagued the sub-period[28] 2006-2011 the results are much stronger than in any other sub-period. One reason is of course the shift of importance for some variables, New Home Sales and Housing Starts have been considered important indicators by market participants for an extended period of time but no study have found them to have a significant effect on the stock market. Here we observe a high level of significance for these two variables, which should not be that surprising giving the housing bust and the problems that it caused for a range of different financial products which increased the financial system's and the overall economy's dependence on the housing market.

[28] That is the sub-period in my data which contains the chaotic years 2007-2011.

However, these tendencies cannot explain why the other variables seem to change their importance for the market. For example the aggregate, standardized announcements, are considerably more significant during this last time period compared with the others and especially the period 2001-2005. This broad change of importance cannot be explained by time-varying betas and does hence point to that the reactions are state-dependent.

Table 6

Table 6 presents the results when the market index is regressed on the unexpected part of the data release (equation 6.). The macroeconomic announcements are all which are released with a monthly frequency. The first column presents the results from the full time-period, the second 1990-1995, the third 1996-2000, the foruth 2001-2005 and the fifth 2006-2011. Coefficients significant at the 5 percentage level are marked bold.

	Full Period		**1990-1995**		**1996-2000**		**2001-2005**		**2006-2011**	
Inflation	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,000	0,580	0,001	0,830	0,003	1,692	0,000	-0,288	-0,001	-0,661
beta	-0,005	-1,492	-0,004	-1,208	-0,008	-0,907	-0,006	-1,364	0,000	0,029
Trade Balance	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,000	0,244	-0,001	-0,919	0,001	0,830	-0,002	-1,508	0,002	1,105
beta	0,001	**1,966**	0,000	-0,715	0,001	1,298	0,001	1,279	0,000	0,847
Retail Sales	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,001	1,238	0,001	1,774	0,002	1,153	0,000	0,238	0,000	-0,207
beta	0,004	**2,527**	-0,001	-0,658	-0,003	-0,537	0,000	0,044	0,011	**3,317**
Non-Farm Payroll	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,000	0,474	-0,001	-0,764	0,006	**3,847**	-0,002	-1,373	0,000	-0,114
beta	0,000	-0,937	0,000	0,845	0,000	**-3,125**	0,000	0,050	0,000	0,600
ISM	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,002	**2,303**	0,001	1,397	0,004	**2,804**	0,002	1,138	0,000	0,188
beta	0,000	1,009	0,000	0,392	-0,001	-1,565	0,001	0,935	0,001	1,223
Housing Starts	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,001	0,830	0,000	0,017	0,002	1,381	0,000	0,067	0,001	0,432
beta	0,000	-0,051	0,001	0,091	-0,020	-0,914	-0,007	-0,468	0,023	0,853
New Home Sales	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,001	**1,949**	0,001	1,536	-0,001	-0,336	0,001	0,690	0,003	**2,197**
beta	0,000	-0,508	0,000	-0,946	0,000	0,476	0,000	-0,665	0,000	0,302
Consumer Confidence	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,002	**2,022**	0,001	**1,949**	0,003	1,724	0,000	-0,077	0,003	1,102
beta	0,000	-0,333	0,000	-1,016	0,000	-0,306	0,000	1,802	-0,001	-1,129
Industrial Production	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**	**Coef**	**t**
Inter.	0,000	0,247	0,000	-0,135	0,001	0,620	0,000	0,264	-0,001	-0,442
beta	-0,002	-0,872	0,001	0,198	0,001	0,118	0,004	1,024	-0,007	-1,818

When examining the reactions of a broad value-weighted market index to the same unexpected announcements as in equation 6, see Table 5 and 6, some of the tendencies observed using individual stock returns are present. With the index as the dependent variable, Retail Sales, Trade Balance and the aggregate announcements are all significant at the 5 percent level. Retail Sales and the aggregate are also significant at the 5 percent level for the sub-period 2006-2011. The Retail Sales beta is once again 1.1 percent and economically significant for the last sub-period. The beta for Trade Balance is 0.1 percent, the Trade Balance have a 10 times higher standard deviation of the estimated unexpected component of the reported value which roughly puts it in the same category of economic significance as Retail Sales. The other variables in the full period or the sub-periods show no sign of affecting the market returns in a simple fashion. The fact that the aggregate seems to affect stock returns but a high portion of the individual variables does not, points to a weak general relationship between announcements and returns with a high degree of dependence of in which situation the market and the economy is currently in.

The regressions with state-dummies confirm the suspicions, many of the announcements seems to generate quite different stock reactions depending on if the economy is in an expansion or a contraction phase. Non-Farm Payrolls and New Home Sales are the only two announcements that do not have considerably different betas for the different states. Since both states for New Home Sales produces similar betas one can conclude that the earlier observed difference across time-periods are not directly caused by the recession in the latest sub-period but rather the crucial role the housing market played during the Credit Crisis. It is also worth noting that Non-Farm Payrolls does not show differences between states of the economy given the strong indication that it in fact does in Cenesizoglu (2011). One can also note that the Federal Funds Rate mostly plays an important role during recessions. When in an expansion state, the second method for calculating statistical significance does not produce t-values acceptable at the 5 percent level. That is, even though increases of the Federal Funds Rate should depress stock prices no matter market conditions, it only reacts strongly in bad times. Since most policy interventions from the Federal Open Market Committee during recessions are decreases of the Federal Funds Rate this means that stocks reaction are most significant when FOMC, unexpectedly, does not lower rates enough or leave them unchanged.

Table 7

Table 7 presents the results when the return of each individual stock is regressed on the state-dependent unexpected part of the data release (equation 9.). The coeffients presented are the averages from all regressions. Two different t-statistics are presented: the t-statistic on the same row as the coefficient is the average t-statistic (equation 12.) while the t-statistic on the row below is the t-statistic of average coefficients (equation 13.). The first column for each variable uses the NBER definition of a contraction and the second column uses the probabilities estimated with a Markov Switching Model for Industrial Production Growth. Coefficients significant at the 5% level are marked bold.

Inflation				
	Coef	**t**	**Coef**	**t**
Intercept	0,001	0,190	0,001	0,118
Expansion Beta	-0,003	-0,330	-0,002	-0,257
		-17,807		**-12,343**
Contraction Beta	-0,002	-0,094	-0,034	-0,752
		-1,945		**-12,981**
Exp. Beta - Con. Beta	-0,002	**-2,069**	0,032	**12,207**

Consumer Confidence				
	Coef	**t**	**Coef**	**t**
Intercept	0,002	0,695	0,002	0,843
Expansion Beta	0,000	0,284	0,000	0,299
		19,405		**18,626**
Contraction Beta	0,000	-0,393	0,000	0,109
		-5,028		**8,610**
Exp. Beta - Con. Beta	0,000	**10,500**	0,000	**-3,127**

Trade Balance				
	Coef	**t**	**Coef**	**t**
Avg α	0,000	0,024	0,000	0,034
Expansion Beta	0,000	0,119	0,000	0,167
		9,667		**13,519**
Contraction Beta	0,001	0,647	0,002	1,001
		5,918		**9,364**
Exp. Beta - Con. Beta	-0,001	**-4,884**	-0,001	**-8,169**

Retail Sales				
	Coef	**t**	**Coef**	**t**
Avg α	0,001	0,907	0,001	0,218
Expansion Beta	-0,001	-0,115	-0,001	-0,045
		-10,091		**-5,751**
Contraction Beta	0,012	1,325	0,019	**2,211**
		18,210		**39,966**
Exp. Beta - Con. Beta	-0,013	**-19,753**	-0,020	**-40,312**

New Home Sales				
	Coef	**t**	**Coef**	**t**
Intercept	0,002	0,807	0,003	1,025
Expansion Beta	0,000	-0,076	0,000	-0,135
		-0,877		**-5,598**
Contraction Beta	0,000	0,185	0,000	0,447
		-0,938		**15,146**
Exp. Beta - Con. Beta	0,000	0,923	0,000	**-15,611**

ISM				
	Coef	**t**	**Coef**	**t**
Intercept	0,001	0,494	0,001	0,557
Expansion Beta	0,000	0,229	0,001	0,332
		16,209		**26,294**
Contraction Beta	-0,001	-0,317	-0,001	-0,364
		-2,846		**-8,651**
	0,002	**3,898**	0,002	**12,876**

FF				
	Coef	**t**	**Coef**	**t**
Intercept	0,003	1,229	0,003	1,038
Expansion Beta	-0,001	-0,013	-0,001	-0,021
		-0,844		-1,476
Contraction Beta	-0,047	-0,464	-0,358	-1,303
		-11,640		**-26,148**
Exp. Beta - Con. Beta	0,047	**11,385**	0,357	**26,061**

Non-Farm Payroll				
	Coef	**t**	**Coef**	**t**
Intercept	0,001	0,294	0,001	0,269
Expansion Beta	0,000	-0,134	0,000	0,035
		1,472		**13,377**
Contraction Beta	0,000	-0,038	0,000	-0,378
		1,250		0,485
Exp. Beta - Con. Beta	0,000	-0,889	0,000	0,185

Housing Starts				
	Coef	**t**	**Coef**	**t**
Intercept	0,001	0,211	0,001	0,283
Expansion Beta	-0,008	-0,165	-0,002	-0,002
		-13,204		**-3,418**
Contraction Beta	0,046	0,500	0,101	0,216
		10,386		**8,815**
Exp. Beta - Con. Beta	-0,055	**-12,164**	-0,103	**-8,964**

GDP				
	Coef	**t**	**Coef**	**t**
Intercept	0,002	0,446	0,002	0,464
Expansion Beta	0,001	0,173	0,001	0,313
		6,964		**12,175**
Contraction Beta	-0,003	-0,301	-0,005	-1,057
		-5,660		-0,603
Exp. Beta - Con. Beta	0,003	**7,158**	0,007	0,760

Other announcements seem to instead of carrying different importance, having a reversed meaning depending on the state of the economy. Consumer Confidence, Retail Sales, Housing Starts, ISM and advanced GDP all have different signs depending on the state whilst both betas are significant. Retail Sales and Housing Stars have the expected sign with regard to earlier studies which have found that good news in expansions are bad for stocks while good news in contractions also is god news for stocks. Retail Sales in contrast followed the results from the first regression more closely and with the longest time-period of a contraction occurring during the latest sub-period, the positive contraction-beta helps explain the large discrepancies between the sub-periods from the first regression. Likewise the expansion-beta was significant and negative.

Consumer Confidence, ISM and advanced GDP did not follow the general earlier findings of state-dependence of announcement but generated the opposite, negative betas in contractions and positive betas in expansions. The GDP coefficients could be explained through expectations of Federal Funds Rate, that a faster recovery than expected could stop the Federal Reserve from easing the Monetary Policy with its benefits for stock prices. The reason behind the betas for Consumer Confidence and ISM are harder to deduct since they are not as interconnected with the Federal Funds Rate as GDP. They are both however forward-looking and it is noteworthy that these two as a group react differently than the rest of the announcements. The one-sided results for Trade Balance are easier to draw conclusions from. The beta is positive and significant for both states indicating that decreases of the Trade Deficit is always good news for American stocks. Most of the results are robust to changing the definition of a contraction. The results for Inflation, Consumer Confidence, New Home Sales, Non-Farm Payrolls and GDP do however experience some changes. The months that no longer are defined as contractions are the months from July 1990-March 1991, March 2001-November 2001, and December 2007-August 2008. For inflation, the results are stronger for contractions and the difference between expansions and contractions are positive instead of negative as with the NBER definition. Consumer Confidence also have a different sign on its estimated beta for contractions, instead of negative as with the NBER definition it is positive and stronger than for expansions. New Home Sales does also show different results, with significant coefficients for both expansions and contractions. This result is in line with the discussion above that the main reason for differences for New Home Sales are due to the greater importance of the variable rather than the state of the economy, since the second definition of contractions has a higher weight on the crisis 2007-2009 than the first definition. Moreover, Non-Farm Payrolls has a significant expansion beta in with the second definition and the negative contraction beta for GDP is no longer significant. The results for the other variables are similar with both definitions. Some of the results could however be affected by differences in the unexpected component of an announcement between states of the economy. In Table 1. the mean and standard deviation for the unexpected component for announcements are presented. Trade Balance has for example a positive mean in contractions but negative in expansions. Similar differences are present for most of the variables. This does not have to be a problem for the interpretation of the results as long as the estimates are equally efficient in both expansions and contractions. But if the forecasters put in a greater effort when the economy is in a bad state this could create problems with the estimation which potentially could affect the results.

1.4.2 Second-step Regressions

The results from the second-step regression, when the betas from Section A. are regressed on firm-specific variables, do not show any unified pattern for any of the variables but a set of firm-characteristics show some explanatory power. The results are presented in Table 8. The proxy for firm-size, the log of Market Value, is significant at the 10 percent level for most announcements: Inflation, Trade Balance, Retail Sales, ISM and Consumer Confidence. Inflation and Trade Balance had betas both significant and the same sign for the state-dependent specification. For each of these two variables the size of the firm has a mitigating effect on the reaction. Its coefficient is positive for Inflation and negative for Trade Balance. Since most estimated contraction and expansions betas for Inflation were negative this suggests that larger firms have a smaller reaction to inflation news. Likewise for Trade Balance, both the average expansion and contraction beta were positive which suggests that large firms do not react strongly to Trade Balance news while small firms do. The same observation can also be done for Book-to-Market independently of their size; growth firms tend to react more to Inflation and Trade Balance announcements than Value Firms.

Table 8

Table 8 displays the results when the betas from the first regression are used as dependent variables in a regression with firm characteristics as independent variables, the years are used as controls. The results for all first step-regressions are reported with each coefficient and its t-statistic. Coefficients that are significant on the 5% level are marked bold. The coefficients are scaled with 100.

	Inflation	Trade Balance	Retail Sales	Non-Farm Payroll	ISM	Housing Starts	New Home Sales	CC
Acid	-0,018	-0,003	-0,012	0,000	0,002	-0,050	0,000	0,000
	-1,479	**-2,093**	**-2,057**	-1,654	**2,191**	-1,374	**1,947**	0,782
D/E	-0,009	0,003	0,005	0,000	-0,003	-0,143	0,000	0,002
	-0,478	1,603	0,551	0,254	**-1,933**	**-2,628**	-0,743	**2,441**
B/M	0,021	-0,005	0,013	0,000	0,002	0,087	0,000	0,000
	1,587	**-2,675**	**1,913**	0,973	**2,098**	**1,976**	1,172	-0,757
log(Mkt Val)	0,021	-0,003	0,019	0,000	0,005	0,020	0,000	-0,001
	1,684	**-2,232**	**2,544**	-0,654	**4,294**	0,502	-1,644	**-2,084**
Illiq	0,145	-0,039	0,098	-0,001	0,065	1,128	-0,002	0,010
	0,474	-0,962	0,481	-1,087	**2,249**	1,059	**-2,035**	0,772

Other literature (Tetlock, 2010) has found the market liquidity of a firm to be of high importance in explaining reactions to firm-specific news. With this specification the variable Illiq is significant for

ISM and New Home Sales but not for the other variables which can be argued carries more importance to the economy. The coefficient for ISM has the right expected sign, liquid stocks are not affected as much by the unexpected component of ISM announcements as illiquid stocks. The coefficient for New Home Sales is however not of the expected sign, illiquid stocks have lower betas. As noted in Chapter III. Section D. some of the estimated betas are lost when proceeding from the first step regressions to the second step regression since only the intersection between the CRSP library and COMPUSTAT library is used. Small and illiquid firms are likely to be the ones that are not part of this intersection why, together with the results for ISM and New Home Sales, the hypothesis that illiquid firms react stronger to macroeconomic news cannot be fully discarded.

1.4.3 Sorting Procedure

If there are some underlying risk-factor that causes different stocks to react differently and with a different magnitude to macroeconomic announcements this should show up in the return for these stocks. According to results presented in Table 9 and Table 10, none of the stocks show signs of having neither contemporaneously or out-of-sample returns that are dependent on their reactions to macroeconomic announcements.

Table 9

In Table 9 the stocks are sorted with respect to their beta from the first regression (equation 6.). The regressions are performed for rolling 5 year periods from 1990-1994 to 2007-2011. For each time period the stocks are sorted into deciles and the in-sample as well as out-of-sample return is calculated. At the end the returns for each decile are averaged across all time-periods. Below the results from this sorting procedure are presented for the Inflation, Trade Balance, Retail Sales and Non-Farm Payroll regressions. Both Equally Weighted and Value Weigthed returns are presented. The difference in returns between the 10th and 1st decile and the difference in returns for the 3 highest deciles and 3 lowest deciles and their Welch t-stats (equation 14.) are presented in the right most columns.

	Inflation													
	Deciles													
	1	2	3	4	5	6	7	8	9	10	10-1	t-stat	10:8 - 3:1	t-stat
	Equally Weigthed													
Out-of-Sample	0,13%	0,17%	0,16%	0,13%	0,16%	0,12%	0,13%	0,17%	0,04%	0,17%	0,04%	0,17	-0,03%	-0,10
In-Sample	0,26%	0,28%	0,33%	0,20%	0,20%	0,28%	0,35%	0,26%	0,30%	0,20%	-0,06%	-0,27	-0,04%	-0,16
	Value Weigthed													
Out-of-Sample	0,31%	0,62%	0,33%	0,42%	0,41%	0,51%	0,43%	0,52%	0,56%	0,54%	0,23%	1,23	0,12%	0,58
In-Sample	0,93%	0,78%	0,76%	0,70%	0,91%	0,82%	0,83%	0,62%	0,76%	0,96%	0,04%	0,14	-0,04%	-0,17
	Trade Balance													
	Equally Weigthed													
Out-of-Sample	0,10%	0,20%	0,19%	0,11%	1,13E-03	0,19%	0,22%	0,30%	0,28%	0,18%	0,08%	0,28	0,09%	0,37
In-Sample	0,28%	0,31%	0,39%	0,28%	0,35%	0,33%	0,31%	0,25%	0,25%	0,24%	-0,04%	-0,15	-0,08%	-0,32
	Value Weigthed													
Out-of-Sample	0,43%	0,58%	0,62%	0,44%	0,47%	0,47%	0,49%	0,43%	0,52%	0,41%	-0,02%	-0,08	-0,09%	-0,42
In-Sample	0,91%	0,73%	0,74%	0,78%	0,73%	0,85%	0,89%	0,98%	0,79%	0,85%	-0,06%	-0,20	0,07%	0,29
	Retail Sales													
	Equally Weigthed													
Out-of-Sample	0,14%	0,07%	0,11%	0,09%	0,05%	0,15%	0,11%	0,07%	-0,02%	0,18%	0,03%	0,12	-0,03%	-0,11
In-Sample	-0,05%	0,05%	0,21%	0,16%	0,16%	0,18%	0,19%	0,17%	0,01%	0,04%	0,09%	0,37	0,00%	0,02
	Value Weigthed													
Out-of-Sample	0,38%	0,44%	0,51%	0,24%	0,55%	0,36%	0,44%	0,28%	0,36%	0,41%	0,02%	0,10	-0,10%	-0,49
In-Sample	0,54%	0,69%	0,81%	0,73%	0,89%	0,78%	0,65%	0,80%	0,64%	0,87%	0,33%	1,41	0,09%	0,39
	Non-Farm Payroll													
	Equally Weigthed													
Out-of-Sample	0,13%	0,13%	0,14%	0,11%	0,22%	0,21%	0,22%	0,11%	0,10%	-0,01%	-0,14%	-0,48	-0,07%	-0,25
In-Sample	0,30%	0,27%	0,28%	0,32%	0,40%	0,26%	0,30%	0,26%	0,22%	0,20%	-0,10%	-0,45	-0,06%	-0,25
	Value Weigthed													
Out-of-Sample	0,61%	0,29%	0,13%	0,48%	0,53%	0,52%	0,61%	0,46%	0,22%	0,56%	-0,05%	-0,17	0,07%	0,27
In-Sample	0,75%	0,74%	0,89%	0,92%	0,91%	0,58%	0,73%	0,73%	0,76%	0,93%	0,18%	0,64	0,02%	0,06

The stocks sorted on betas for some macroeconomic announcements show up a minor spread between the first and tenth decile, either for equally-weighted or value-weighted and some displays an equally minor spread between the three first deciles and three last deciles. In the cases this is true, both for contemporaneous returns and out-of-sample returns, the results are not consistent and no clear monotonic pattern emerge from the sorting. Only the value-weighted out-of-sample differences for Consumer Confidence have t-stats above 1, for all other variables in all other settings the t-stats are below 1. The comparison between the tenth and first decile is the most significant one for Consumer Confidence, but only with a t-stat of 1.41.

Table 10

In Table 10 the stocks are sorted with respect to their beta from the regression (equation 6.). The regressions are performed for rolling 5 year periods from 1991-1995 to 2007-2011. For each time period the stocks are sorted into deciles and the in-sample as well as out-of-sample return is calculated. At the end the returns for each decile are averaged across all time-periods. Below the results from this sorting procedure are presented for the ISM, Consumer Confidence, New Home Sales, and Housing Startsregressions. Both Equally Weighted and Value Weigthed returns are presented. The differences between the 10th and 1st portfolio and the differences between the three highest portfolios and the three lowest portfolios are presented in the right most columns together with their Welch t-stat (equation 14.).

	Deciles													
	1	2	3	4	5	6	7	8	9	10	10-1	t-stat	10:8 - 3:1	t-stat
ISM														
Equally Weigthed														
Out-of-Sample	0,12%	0,02%	0,02%	0,06%	0,09%	0,11%	0,17%	-0,02%	0,07%	0,07%	-0,05%	-0,16	-0,01%	-0,03
In-Sample	-0,01%	0,11%	0,09%	0,12%	0,11%	0,01%	0,08%	0,10%	0,06%	-0,04%	-0,03%	-0,11	-0,02%	-0,09
Value Weigthed														
Out-of-Sample	0,65%	0,50%	0,18%	0,20%	0,42%	0,48%	0,52%	0,46%	0,35%	0,42%	-0,23%	-0,87	-0,03%	-0,13
In-Sample	0,83%	0,67%	0,77%	0,83%	0,84%	0,80%	0,76%	0,73%	0,76%	0,95%	0,12%	0,41	0,05%	0,19
Consumer Confidence														
EW														
Out-of-Sample	0,06%	0,03%	0,09%	0,15%	-0,03%	0,05%	0,05%	0,09%	0,14%	0,02%	-0,04%	-0,15	0,03%	0,11
In-Sample	-0,01%	0,14%	0,08%	0,14%	0,08%	0,11%	0,09%	0,14%	-0,01%	-0,07%	-0,07%	-0,30	-0,05%	-0,25
VW														
Out-of-Sample	0,24%	0,20%	0,42%	0,66%	0,51%	0,55%	0,73%	0,33%	0,66%	0,61%	0,36%	1,41	0,24%	1,03
In-Sample	0,69%	0,94%	0,84%	0,82%	0,86%	0,83%	0,82%	0,98%	0,71%	0,69%	0,00%	0,00	-0,03%	-0,12
New Home Sales														
Equally Weigthed														
Out-of-Sample	0,05%	0,20%	0,10%	0,17%	1,35E-03	0,14%	0,14%	0,14%	0,12%	0,18%	0,13%	0,45	0,03%	0,11
In-Sample	0,10%	0,28%	0,29%	0,20%	0,22%	0,22%	0,24%	0,20%	0,13%	0,10%	0,00%	0,00	-0,08%	-0,36
Value Weigthed														
Out-of-Sample	0,33%	0,60%	0,45%	0,32%	0,45%	0,35%	0,46%	0,54%	0,63%	0,41%	0,08%	0,25	0,07%	0,29
In-Sample	0,81%	0,86%	0,73%	0,74%	0,90%	0,89%	0,80%	0,75%	0,61%	0,73%	-0,08%	-0,33	-0,11%	-0,42
Housing Starts														
Equally Weigthed														
Out-of-Sample	-0,03%	0,13%	0,06%	0,12%	0,14%	0,17%	0,10%	0,18%	0,13%	0,11%	0,14%	0,50	0,08%	0,32
In-Sample	0,19%	0,15%	0,25%	0,27%	0,33%	0,26%	0,30%	0,35%	0,36%	0,31%	0,12%	0,51	0,14%	0,64
Value Weigthed														
Out-of-Sample	0,23%	0,39%	0,38%	0,37%	0,76%	0,51%	0,40%	0,51%	0,32%	0,33%	0,10%	0,42	0,05%	0,23
In-Sample	0,62%	0,60%	0,66%	0,73%	0,88%	0,79%	0,94%	0,82%	1,05%	0,73%	0,11%	0,40	0,24%	0,98

The results in IV.A showed that for a majority of the analyzed announcements the reaction is dependent on the state of the economy. This is however difficult to use in this sorting procedure given the low number of announcement days that occur during a recession in the sample. Recent evidence has also shown that the risk related to Macroeconomic Announcement Days is not the announcement themselves but the fact that there is an announcement (Savor and Wilson, 2012). The fact that state-dependence plays an important role for the estimated betas make this exercise somewhat hard to interpret. While the evidence in Savor and Wilson suggests that one should look in another direction than announcement betas.

1.5 Conclusions and Future Research

The aim of this thesis is to improve the knowledge of how macroeconomic announcements affect stock returns. The main insights from the results are that stocks seem to be affected by macroeconomic announcements, mainly small stocks, and especially that the effect is strongly dependent on the economic state. Although some earlier research, Poitras (2004), had rejected this, it is clear from my results that a number of announcements affect stock prices differently depending on which state the economy is in. The announcements of Retail sales shows the clearest pattern with negative stock responses to unexpected good news in expansions and positive responses to unexpected good news in contractions. The difference between the reactions in a good economic state and the reaction in a bad economic state is also highly significant.

One can also note that the forward-looking indicators, the Consumer Confidence Index and the ISM Index, cause negative stock responses to good news in contractions and positive responses to good news in expansions. The results also suggest that the importance of economic announcements for stocks is far higher during contractions.

As for the general responses, the betas are not significant on average while most of the announcements have average betas that are significantly different from zero. That is, taking the average t-stat for each stock results in insignificant results. But when averaging the estimated betas, that average is statistically different from zero. The results are hence not conclusive but point to the fact that macroeconomic announcements matter for stocks. This result differs from the results when using a value-weighted index as the dependent variable. Since the estimation with each individual stock and the average beta is comparable with an estimation with an equally-weighted index, the difference suggest that small firms reacts stronger to the unexpected part of macroeconomic announcements than large firms do. This helps explaining some of the earlier literature's problems with finding a general, non state dependent, reaction of stock indices to the unexpected part of announcements. The relationship is however complicated and as noted the results get clearer and more statistically significant when easing the restriction of homogenous responses over different economic states.

The second step-regression displayed significant coefficients for four different announcements for the variables size and book-to-market. For the two announcements that affected stock returns the most, the coefficients suggest that large firms and value-firms have smaller reactions to inflation and Trade Balance than small firms and growth-firms do. When sorting stocks according to their macroeconomic betas and placing them into portfolios, no pattern was detected.

Possible extensions of this thesis could be an inclusion of a higher number of announcements, for example, separating the announced value in Trade Balance into Exports and Imports, using more indicators from the Employment Report, and using a higher number of price indices. Another extension would be to allow for asymmetric stock reactions in terms of positive and negative news, both together with state-dependence and without. This would control for clear patterns of the unexpected component in different states of the economy, such that more negative unexpected announcements during recessions does not affect the estimated coefficient for reactions during contraction periods. Moreover, one could also decompose the unexpected announcement into a surprising and an unsurprising part as in Campbell and Sharpe (2007), to control for anchoring bias present among the survey respondents. Another extension could be to test whether the estimated announcement betas can explain priced risk factors instead of analyzing the announcements themselves as potential risk factors. Furthermore, future research in the field could concentrate more on the findings of Savor and Wilson (2012) and analyze why there is a higher return on announcement days independently of the announced values. Apart from their results, findings in Gilbert (2011) of a connection between first reported values of announcements and their revisions, Campbell and Sharpe's (2007) finding of anchoring bias in forecasts, and the possibility that macroeconomic announcements are unambiguous events, discussed in Viale (2009), point to some problems with the event-study approach used in this thesis as well as in the vast majority of related studies. Hence extensions of the IC-approach,[29] suggested by Rigobon and Sack (2008), could help with adding robustness to both my findings and those of related papers. Moreover, stronger results in this sense would also benefit extensions of Savor and Wilson's work, with a better control for the announcement values when analyzing the jump in risk premia and Sharpe-ratio during announcement days as opposed to regular trading days. If high-frequency data is available one could also study the volatility and bid-ask spreads for different stocks with different characteristics when macroeconomic indicators are announced.

[29] See Chapter II. Section A for a discussion and explanation of their method.

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1.7 Appendix

Here are the results from the multiple regression described in III.C.

Table A

Table A presents the results for specification 8. The t-stats on the first row are the average t-stats (equation 10.), the t-stats on the second row are the t-stats for the sample of betas (equation 11.) and t-stats for the state-dependence regression are also calculated according to equation 11.

	Full Period		1990-1995		1996-2000		2001-2005		2006-2011		State Dependence		
Intercept	0,0011	0,85	0,0011	0,56	0,0019	1,00	0,0008	0,53	0,0010	0,75		0,0011	49,61
Consumer Confidence	0,0004	0,01	0,0004	0,00	0,0007	0,07	0,0015	0,41	-0,0014	-0,43	Expansion	0,0012	**17,42**
		6,34		**3,35**		**6,87**		**21,23**		**-12,55**	Contracion	-0,0009	**-4,24**
Housing Starts	-0,0002	0,00	0,0006	0,07	-0,0033	-0,31	-0,0004	-0,05	0,0023	0,38	Expansion	-0,0008	**-9,71**
		-2,64		**4,03**		**-23,39**		**-5,93**		**21,29**	Contracion	0,0053	**8,65**
Inflation	-0,0007	-0,28	-0,0010	-0,28	-0,0009	-0,21	-0,0006	-0,26	-0,0010	-0,28	Expansion	-0,0006	**-12,14**
		-14,06		**-13,21**		**-8,40**		**-11,13**		**-19,12**	Contracion	-0,0014	**-5,58**
Industrial Production	-0,0007	-0,23	-0,0004	-0,01	-0,0012	-0,26	0,0004	0,07	-0,0012	-0,47	Expansion	-0,0006	**-8,31**
		-10,48		**-3,06**		**-11,57**		**5,64**		**-18,05**	Contracion	-0,0001	-0,56
ISM	0,0000	0,06	0,0000	-0,02	-0,0014	-0,29	0,0010	0,24	0,0014	0,38	Expansion	0,0008	**13,46**
		0,28		-0,08		**-14,07**		**14,37**		**17,40**	Contracion	-0,0027	**-6,40**
Non-Farm Payroll	-0,0003	-0,14	0,0002	0,02	-0,0034	-0,72	0,0014	0,13	0,0032	0,47	Expansion	0,0003	**4,55**
		-5,09		1,56		**-40,97**		**16,20**		**25,53**	Contracion	-0,0001	-0,14
New Home Sales	0,0004	0,04	0,0002	-0,01	0,0005	0,06	-0,0004	-0,16	0,0008	0,10	Expansion	0,0003	**4,97**
		7,88		**2,32**		**6,18**		**-9,50**		**11,76**	Contracion	0,0004	0,37
Retail Sales	0,0007	0,45	-0,0004	-0,16	-0,0014	-0,13	-0,0003	-0,05	0,0044	1,51	Expansion	-0,0005	**-8,87**
		11,33		**-4,56**		**-8,95**		**-4,23**		**65,57**	Contracion	0,0047	**20,14**
Trade Balance	0,0010	0,37	0,0010	0,16	0,0011	0,19	0,0009	0,32	0,0013	0,49	Expansion	0,0006	**10,26**
		18,46		**8,29**		**12,03**		**21,18**		**29,60**	Contracion	0,0026	**9,66**
Unemployment Rate	-0,0013	-0,28	-0,0021	-0,42	-0,0006	-0,10	-0,0003	0,00	-0,0019	-0,41	Expansion	-0,0005	**-7,65**
		-20,43		**-19,83**		**-4,73**		**-4,03**		**-28,48**	Contracion	-0,0032	**-7,68**
GDP	0,0001	0,02									Expansion	0,0010	**8,13**
		1,37									Contracion	-0,0002	-0,54

2 Idiosyncratic Higher Order Moments in the Cross-Section of Stock Returns

Abstract

I examine the pricing of idiosyncratic risk, in the form of higher order moments, in the cross section of stock returns. By using the errors when returns are regressed on a 4-factor model, I measure the idiosyncratic volatility, skewness and kurtosis. Using portfolios sorted on the idiosyncratic measures, I find idiosyncratic skewness to be contemporaneously positively correlated with average returns according to a strictly monotonic pattern. The return spread between portfolios with high idiosyncratic skewness and portfolios with low idiosyncratic skewness is high and significant. The results are robust to other pricing anomalies such as size and liquidity and are independent of weighting scheme used. The spreads for idiosyncratic volatility and idiosyncratic kurtosis does not show any clear pattern. The reason for the relationship is not examined but the results could for example be explained by the negative autoregressive coefficient of monthly skewness together with that expected idiosyncratic skewness is priced or by the incompleteness of the asset pricing model used and thus suggesting that some systematic risk factor is omitted.

2.1 Introduction and Related Literature

Since the traditional Capital Asset Pricing Model (CAPM) by Sharpe (1962), Lintner (1965) and Black (1972) a number of different pricing anomalies have been documented with respect to the basic model. Some have been explained by introducing new factors while others remain puzzling. Merton (1973) defined a theoretical framework as an extension of CAPM, Intertemporal Capital Asset Pricing Model (ICAPM), but without specifying the risk factors. Fama and French (1992) continued the work of Merton and found two additional risk factors that where priced in the market with their 3-factor model. The use of the "Small-Minus-Big" portfolio where able to capture some of the associated risk with small firms and the "High-Minus-Low"-portfolio captured the risk associated with firms that had high Book-to-Market (or value stocks). A couple of years later Carhart (1997) as well as Jegadeesh and Titman (1993) found evidence of a fourth priced risk factor which now is commonly used together with the original Fama and French model, the momentum factor. Recent developments have also pointed to a fifth priced risk factor: the liquidity risk factor (see for example Pastor & Stambaugh, 2003).

Recent research in the field have, among other things, been concentrated on modeling asset prices that take into account the distributions specifications for returns which evidently are far away from being normally distributed. The recent credit crisis and the current debt crisis are two events that have contributed to making our historical return distribution even more negatively skewed and leptokurtic. This make the need for a deeper understanding of the preferences of investors in regard to the higher order moments more pressing as well as how these preferences are related to empirical tendencies of stock returns.

Recent models aside, literature during the last years have concentrated on the errors that these models produce. The basic theoretical concept of all the standard models is that investors should only get rewarded for the systematic risk they are exposed to. Other kinds of risks that the models do not price are deemed diversifiable and should hence not command a risk premium. However, a number of studies have found this idiosyncratic part to be priced in the cross section. Merton (1987) argued that idiosyncratic risk, in the form of idiosyncratic volatility, should only remain unpriced in complete markets with perfect information and without frictions since these are the assumptions under which the CAPM is derived. Since markets are not complete, some portion of the idiosyncratic risk could be impossible to diversify away and hence should therefore command a risk premium. Goyal and Santa-Clara (2003) argue that idiosyncratic risk matters when finding that the cross-sectional average of variances predicted future returns. Average stock risk defined in this manner is largely idiosyncratic. Their findings are however in the time-series relationship between the average risk of stocks and the market return. Bali, Cakici, Yan & Zhang (2005) find these results being limited to that specific procedure and argue that the results lack external validity. That is; small and theoretically sound modifications of the empirical framework produces different results. The results are, for example, different when the full stock universe is used and when controlling for the risks associated with illiquidity.

Ang, Hodrick, Xing & Zhang (2006) found that idiosyncratic volatility is priced in the cross-section and that ranking stocks with respect to idiosyncratic volatility yields an expected return premium from low idiosyncratic volatility to high idiosyncratic volatility. This is the opposite of the relationship proposed by Merton. The results cannot be explained by size, book-to-market, liquidity and a set of other factors that literature has found to be priced in the cross-section. They also find that innovations in expected aggregate volatility is priced, hence this cannot explain the puzzling results for idiosyncratic volatility. In a later paper they also found the same relationship to be true in all G7 countries and that stocks with high idiosyncratic volatility are highly correlated with stocks in other countries with high idiosyncratic volatility suggesting that the results are due to a significant economic risk factor omitted from the regular asset pricing models. In the later paper they also increase the number of robustness test (Ang, Hodrick, Xing & Zhang, 2009). The robustness tests in the later paper are important in the light of a paper by Bali & Cakici (2008), which find that idiosyncratic risk and its relationship with stock returns are highly sensitive to different specifications of asset pricing models, sorting procedures, weighting schemes as well as the time-window and frequency used for estimation.

The fact that idiosyncratic risk is priced is a receipt of the failure of today's commonly used asset pricing models and the, to some extent, theoretical motivation behind them. The results of Ang, Hodrick, Xing & Zhang (2006 & 2009) are puzzling but they do not propose a theoretical framework for why investors have a preference for stocks with high idiosyncratic volatility which give the same stocks low future average returns. Jiang, Xu & Yao (2009) proposes that idiosyncratic volatility is related to negative future unexpected earnings surprises, explaining why stocks with high idiosyncratic volatilities have lower average returns.

Given that idiosyncratic risk is defined as the nonsystematic part of the returns, the return volatility with respect to the risk factors that cannot be diversified away, there are other moments than variance that have risks. Literature suggests that investors care about more than the mean and volatility of returns; they also care about the skewness and kurtosis of their return distributions. These two moments are not implicitly diversified away through the same procedure as when dealing with stock volatility, both moments' decreases in a portfolio when the number of stocks increases but since the co-variance, co-skewness and co-kurtosis can have different signs and be of different magnitude minimizing one of the co-moments will not explicitly minimize the others. Therefore an argument could be made that skewness and kurtosis risk should be imbedded in the errors of standard asset pricing models if investors are diversified in a mean-variance setting.

The area of testing how investors are compensated for skewness and kurtosis risks dates back to extended CAPM models by Kraus and Litzenberg (1976), Friend and Westerfield (1980) and Lim (1989) who all find evidence of skewness being a priced risk factor. Guidolin and Timmerman (2008) find that co-skewness and co-kurtosis are priced with the expected sign in time-varying a 4-moment ICAPM. Harvey and Siddique (1999, 2000a and 2000b) have also focused on the role of skewness and its relationship with the risk premium and have found significant results that conditional skewness is priced in the cross-section of equity returns as well as co-skewness. They also find the autoregressive parameter for monthly skewness to be negative. A study by Engle and Mistry (2007) suggested that the two additional risk factors found by Fama and French, the momentum factor found, by Carhart (1997) as well as Jegadeesh and Titman (1993), can be explained by the risk premium that negative skewness demand. They also find that small firms, value firms, highly levered firms and firms with poor credit ratings in general have higher skewness. Findings by Adrian and Rosenberg (2008) suggests that market skewness correlates with a measure for short-run volatility which they found to be a priced risk factor. They interpret their results such that investors are willing to pay for insurance against increases in volatility risk. Chung, Johnson and Schill (2006) documented that including higher order co-moments in an asset pricing model reduces the effect of the Fama and French factors to insignificance and argues that these portfolios are proxies for the co-moment factors which are the real priced factors.

The behavioral evidence of investor preferences when under uncertainty have also found similar result. Barberis and Huang (2001) models an equilibrium model where investors exhibit individual stock accounting as well as loss aversion which are able to capture a significant amount of cross-section tendencies for stock returns. High loss aversion would translate to higher aversion to negative skewness than preference for positive skewness and stocks with this return characteristic should therefore command a risk premium.

Eeckhoudt and Schlesinger (2006) derived theoretically how the common utility functions translates into preferences for returns and how it is connected to lottery pairs which makes it easy to test in experiments. Given the standard utility functions, the hypothesis they derive under an expected utility framework is that the agents should be prudent (prefer positive skewness) and temperate (prefer low kurtosis). Deck and Schlesinger (2008) tested this hypothesis in a number of lottery experiments. They find evidence for agents being prudent but find no evidence for temperance, in contrast they find that agents are intemperate. The intemperance does however vanish when the lottery stakes are increased. The only utility framework that captures these tendencies is the Cumulative Prospect Theory developed by Kahneman and Tversky (1992). Barberis and Huang (2008) undertakes the task of analyzing the asset pricing implications of Cumulative Prospect Theory and their model predicts that not only is the skewness of a firm priced, it is overpriced.

The main implication of CPT is that improbable events get a much higher weight, agents are highly averse against large negative events and seeks large positive events. If this would turn up in asset prices the combination of positive skewness and high kurtosis would be attractive whilst negative skewness in combination with high kurtosis should command a high risk premium. The aversion against the latter is however much stronger than the preference for the former. The stakes effect that is present in the experiment of Deck & Schlesinger (2010) also has implications for asset pricing. It have been found that the utility functions for professional investors as opposed to retail investors are quite different, with professional investors being more mean-variance optimizers while some retail investors are "lotto investors" and actively seek the combination of high skewness and high kurtosis (Mitton & Vorkink, 2007).

Boyer, Mitton and Vorkink (2010) undertakes an empirical test given the theoretical motivation of Mitton & Vorkink (2007) that high expected idiosyncratic skewness generates low expected returns. They model idiosyncratic skewness with the help of lags and firm-level variables and find results strengthening the hypothesis. The results holds true while separating the effect of expected skewness and idiosyncratic volatility. The relationship between the variables is quite strong and they suggest that investors take on high idiosyncratic volatility stocks in spite of the low return since they gain exposure to high expected skewness.

Chang, Christoffersen and Jacobs (2010) find that sorting stocks after their sensitivities to innovations in volatility, skewness as well as kurtosis independently commands risk premiums. It's an extension of the first part of the Ang, Hodrick, Xing & Zhang (2006) paper. They find that the sensitivity to innovations in all three variables carries a negative price of risk. I.e. that not only is aggregate volatility priced but also aggregate skewness and kurtosis. Agarwal, Bakshi and Huij (2008) find similarly that hedge funds are exposed to a model using market excess return and innovations in the second, third and fourth order moments.   Within the above context there exists a need of a deeper understanding of the relationship between idiosyncratic skewness and kurtosis and the cross section of stock market returns. Especially how well the regular two-moment asset pricing models are able to capture the risks associated with the third and fourth moment that have been shown to matter both in a behavioral setting as well as an empirical setting. The aim of this paper is to extend the analysis of idiosyncratic second order moments made by Ang, Hodrick, Xin and Zhang (2006) and incorporate the idiosyncratic third and fourth moment, skewness and kurtosis in the analysis. Both in terms of contemporaneously and future expected returns. Since there is a wide spread disagreement about the sign of the relationship, I aim to use a modified version of the definition of idiosyncratic risk as well as a contrasting estimation procedure. The results of Chang, Christoffersen and Jacobs (2010) suggests that not only is aggregate volatility priced but also aggregate skewness and kurtosis, which suggests that regular models could misprice idiosyncratic skewness and kurtosis in the same way they according to Ang, Hodrick, Xing & Zhang (2006) misprice idiosyncratic volatility. If the idiosyncratic third and fourth moments are priced then it could suggest that the returns skewness and kurtosis (or the underlying variables that drives the statistical measures) are mispriced or even unaccounted for in the regular Asset Pricing Models. The result of Engle and Mistry (2007) also suggest that the if the risks with small stocks, value stocks, levered firms and firms with poor credit ratings are not fully accounted for by the Fama and French 3 (4)-factor model then their skewed returns characteristic would be transferred to the errors.

Ultimately the focus of this paper is on how the cross-section of stock returns is related to the idiosyncratic higher order moments both contemporaneously and out-of-sample. It differs from other studies in the field on three important points: i) the focus lie on all three commonly used higher order moments (as opposed to Ang, Hodrick, Xin & Zhanh, 2006). ii) It treats idiosyncratic skewness in the same way as idiosyncratic volatility and not the expectation of the variable (as in Boyer, Mitton & Vorkink, 2010) iii) It incorporates the Momentum factor into the baseline regression which errors are used to estimate idiosyncratic risk. It does also by extension analyze the ability of standard two moment asset pricing models to price higher order moments.

The paper will be organized as follows: Section II introduces the empirical framework and the data used for the analysis. Section III presents the empirical results. Section IV concludes the paper.

2.2 Empirical Framework and Data

2.2.1 Benchmark Regression

To test if idiosyncratic skewness and kurtosis are priced risk factors in an ICAPM framework (Merton, 1973), one have to define a standard model where the residuals should be used, that is to which risk factors are the residuals deemed to be idiosyncratic. Since the error series are highly dependent on the included risk factors I strive to use as a complete model as possible. Given the well documented empirical failure of CAPM, I use the Fama-French Model proposed by Fama & French (1993) with the addition of the momentum factor found by Jegadeesh & Titman (1993) as well as Carhart (1997).

$$R_{i,t} - R_{f,t} = \beta_{M,i}\left[R_{mkt,t} - R_{f,t}\right] + \beta_{S,i}\left[R_{smb,t}\right] + \beta_{V,i}\left[R_{hml,t}\right] + \beta_{mom,i}\left[R_{mom,t}\right] + \varepsilon_{i,t} \qquad (1)$$

Where R_{mkt}, R_{smb} and R_{hml} are the market excess return proxy, the excess return of small stocks over big stocks (small minus big) and the excess return of high market-to-book stocks over low market-to-book stocks (high minus low). R_{mom} is the excess return of the past years stocks with highest return over the past years stocks with lowest return.

The regression initiates at the start of each month and ends a full year later. Hence the estimation period depends on the number of trading days during the 12 months, ranging from 224 observations (and start at t=-223) up to 255 (start at t=-254). With these relatively short time-windows I seek to avoid problems with time-varying betas whilst having as a high number of observations as possible to get greater statistical power and significance for the estimates. This is crucial for skewness and kurtosis which tends to be noisier than volatility and hence requires more observations. Volatility generally can be well estimated with shorter time-windows which make a shorter time-window more appealing if the focus is on that specific order moment, since the focus of this paper is on idiosyncratic skewness and kurtosis the longer time-period is chosen.

2.2.2 Estimating Idiosyncratic risk

Using the residuals series of (1) I will rank stocks with respect to their idiosyncratic risk in a number of different ways. The idiosyncratic measures describe the firm-specific risks that the systematic risk factors do not account for. The estimated idiosyncratic second, third and fourth moment follows the non-parametric equations below:

$$\text{Idiosyncratic Volatility}_{\mathrm{i}} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} \varepsilon_t^2} \quad (2)$$

$$Idiosyncratic\ Skewness_i = \frac{T}{(T-1)(T-2)}\sum_{t=1}^{T}\left(\frac{\varepsilon_{i,t}}{\widehat{\sigma_i}}\right)^3 \quad (3)$$

$$Idiosyncratic\ Kurtosis_i = \frac{T(T+1)}{(T-1)(T-2)(T-3)}\sum_{t=1}^{T}\left(\frac{\varepsilon_{i,t}}{\widehat{\sigma_i}}\right)^4 - \frac{3(T-1)^2}{(T-2)(T-3)} \quad (4)$$

$$Idiosyncratic\ Relative\ Upside\ Volatility_i = \sqrt{\sigma^2_{\varepsilon_{i,u}}} - \sqrt{\sigma^2_{\varepsilon_{i,d}}} \quad (5)$$

Equations (2)-(4) are the standard measures for second, third and fourth moment. Equation (5) is a risk measure which incorporates both volatility and skewness, the second part can be recognized as the denominator of the Sortino-Ratio but the full measure (or rather the negative of the full measure, relative downside volatility) has recently also been found to add value in modeling downside risk (Feunou, Jahan-Parvar & Tedongap, 2012). Chen, Ang & Zheng (2009) find that a relative Downside Risk measure, *Downside Beta* is priced in the cross-section and cannot be explained by other popular factors, including co-skewness. It manages to capture both some of the risks related to volatility as well as the asymmetry of the return distribution. Since investors in a regular setting should care far more about downside volatility than upside volatility it is an interesting risk measure and it have been shown to add some value in the regular cross-section and hence its idiosyncratic counterpart could add value in this setting. It will mainly be treated as an alternative measure of asymmetry to skewness.

2.2.3 Sorting Procedure

When the idiosyncratic risks above are estimated, portfolios are created with three different basic procedures; Single-Sorting with respect to the variables of interest, Single-Sorting within already sorted quintiles of risks that have been found to be priced and by Double-Sorting with respect to the variables of interest. The single-sorting procedure will be performed on the four (equations (2)-(5)) variables into quintiles to see if there is a significant spread in returns from low to high for idiosyncratic volatility and idiosyncratic kurtosis and from high to low for idiosyncratic skewness and idiosyncratic relative upside volatility. The other single-sorting procedure will be performed with respect to idiosyncratic skewness, kurtosis and relative upside volatility within the sorted idiosyncratic volatility quintiles and idiosyncratic skewness within quintiles sorted on Market Value and the illiquidity measure Illiq. This is done to control for the risks associated with Idiosyncratic Volatility, Size and Illiquidity. Eg. by first sorting on idiosyncratic volatility and then idiosyncratic skewness, I get quintiles with dispersion in idiosyncratic skewness simultaneously with homogenous idiosyncratic volatility measures and can separate the idiosyncratic skewness risk from that of idiosyncratic volatility.

Double-sorting will be done with respect to the combinations of: idiosyncratic skewness together with idiosyncratic kurtosis and volatility and idiosyncratic relative upside volatility together with idiosyncratic kurtosis and volatility. This procedure follows the regular Double-Sorting procedure of Fama & French (1996) and is done to separate the risks of the measures from each other. All the stocks are sorted independently with respect to two variables into terciles, the stocks are then placed into portfolios determined by the intersection of the breakpoints for the two measures. In this setting both variables can be analyzed, for example double sorting on idiosyncratic volatility and skewness will yield idiosyncratic skewness (idiosyncratic volatility) dispersion along each row (column) while holding the idiosyncratic volatility (skewness) measures fixed within the analyzed row (column). The drawback from separating the risks in this way is that each portfolio will contain different number of stocks which could create problems with too few stocks in the "corner bins" of a double sorted matrix if many quantiles are used. If a fewer number of quantiles are used the procedure could be exposed to not acquire homogenous measures of the non-analyzed variable. I try to minimize the drawbacks by sorting the stocks into terciles which hopefully will generate a large enough number of observation in every matrix "bin" and at the same time get homogenous measures for of one of the variables across rows (columns) with dispersion for the other variable across columns (rows).

The Illiquidity Measure "Illiq" is defined and proven to be priced in Amihud (2003). The measure is defined as following in a regular trading month:

$$Illiq_{i,t}{}^{30} = \frac{1}{N} * \sum_{t-N+1}^{t} \frac{|r_{i,t}|}{Dollar\ Trading\ Volume_{i,t}}$$

Low Illiq values indicates liquid stocks while a high Illiq value indicate an illquid stock.

2.2.4 Contemporaneous and Out of Sample Analysis

The sorting procedure described above is carried out with the residuals from the regressions for each of the 541 time-periods. Then the average returns for month *t=0 and t=1* for each portfolio is calculated before an average is taken for the full time-period with respect to both *t:s*. Since daily data is used to estimate the idiosyncratic measures this means that the compounded return from, approximately, t=-21 to t=0 equals month t=0 and from t=1 to t=22 equals month t=1. Tendencies and patterns from high to low returns and characteristics of returns are then analyzed to give insight on the relationship of idiosyncratic risk and returns. All averaging described above are primarily done on an equally weighted basis, some of the averaging are also undertaken on a value-weighted basis to add robustness to the results. This is an important robustness check with respect to the prior method critique found in Bali and Cakici (2008). The equally-weighted returns analyze the relationship of the average stock rather than the average invested dollar that the value-weighted returns yields. Both methods have been used in prior research and Ang et al (2009) find that the weighting procedure

[30] When the return is equal to zero the trading day is excluded from the measure and if the Dollar Trading Volume is equal to zero it is set equal to the lowest non-zero dollar trading volume of that month so that really illiquid stocks doesn't get a downward bias and seem to be more liquid than they are.

does not change the significance of their results even though the value weighted procedure generates higher significance.

The contemporaneous analysis focuses on mispricing and the analysis of the return of when *t=0*. The out of sample analysis of *t=1* handles future expected returns and to a higher extent demand forward looking idiosyncratic risk measures to give real insight outside of trivial prediction. In this setting the expected *t=1* measures is simply the last observation, which creates some interpretation problems since the measures have been shown to be time-varying and more sophisticated modeling approach would likely yield more robust estimates. With this in mind the majority of the attention will be on the contemporaneous analysis.

2.2.5 Data

The full U.S. stock universe (AMEX, NYSE and NASDAQ) is used and collected from CRSP library. The returns, Permanent Company Number (permno), prize, trading volume and number of shares outstanding are collected for each day and each stock. The factor portfolios and the risk-free rate are the portfolios and the risk-free rate proxy constructed by Fama and French and collected from their database. The data sets starts in January 1966 and uses observations up until December 2011. Thus resulting in 541 different time-periods were the regressions are estimated. In Table I below, the main characteristics of the data set are presented.

Table I - Data Description

In the below table the results from the daily regressions are represented. The valus are averaged on an equally weighted basis for each time-period and then averaged across all months. The first column presents the return, volatility, skewness, kurtosis and relative downside volatility. The second column presents the alpha and the factor sensitivity to the market portfolio, the Small-Minus-Big and High-Minus-Low portfolios of Fama French and the Momentum Portfolio. The third column presents the behavior of the residuals from the regressions with the volatility, skewness, kurtosis and relative upside volatility as well as the number of firms. The returns, alphas, volatility and relative downside volatility are yearly scaled.

Return Series		Regressions		Residual Series - Idiosyncratic	
Return	13,25%	**Alpha**	7,82%	**Volatility**	47,10%
Volatility	50,31%	**Beta - Mkt**	0,85	**Skewness**	0,60
Skewness	0,58	**Beta - SMB**	0,69	**Kurtosis**	10,16
Kurtosis	10,12	**Beta - HML**	0,18	**Relative Upside Volatility**	9,22%
Relative Downside Volatility	-12,08%	**Beta - Mom**	-0,06	**Number of Firms**	5478

2.3 Results

2.3.1 Single Sorting

Table II displays the descriptive statistics for when stocks are sorted into quintiles for each measure. Table III presents the contemporaneously results when portfolios are created by single-sorting with respect to the four variables of interest. Table IV presents the out-of-sample results.

Table II - Data descriptions of sorted portfolios

The table below presents the descriptive statistics of the quintiles when sorted on Idiosyncratic Volatility, Idiosyncratic Skewness, Idiosyncratic Kurtosis and Idiosyncratic Upside Volatility from low (1) to high (5). The valus are averaged on an equally weighted basis for each time-period and then averaged across all months. The first column presents the return, volatility, skewness, kurtosis and relative downside volatility. The second column presents the alpha and the factor sensitivity of the market portfolio, the Small-Minus-Big and High-Minus-Low portfolios of Fama French and the Momentum Portfolio. The third column presents the behavior of the residuals from the regressions with the volatility, skewness, kurtosis and relative upside volatility as well as the number of firms. The returns, alphas, volatility and relative downside volatility are monthly scaled.

Panel A - Idiosyncratic Volatility														
	In Sample Return Statistics					**Idiosyncratic**				**Beta**				
Quintile	**Mean**	**Vol**	**Skew**	**Kurtosis**	**RDV**	**Vol**	**Skew**	**Kurtosis**	**RDV**	**Alpha**	**Mkt**	**SMB**	**HML**	**MOM**
1	0,55%	5,18%	0,29	8,60	-0,45%	5,95%	0,25	9,00	-0,61%	0,2%	0,58	0,22	0,20	-0,02
2	0,82%	8,30%	0,410	8,69	-0,94%	9,23%	0,38	8,62	-1,24%	0,4%	0,82	0,49	0,22	-0,03
3	0,98%	11,56%	0,523	9,54	-1,60%	12,63%	0,50	9,30	-2,10%	0,5%	0,95	0,74	0,18	-0,04
4	0,97%	16,00%	0,644	10,52	-2,67%	17,07%	0,64	10,27	-3,58%	0,4%	1,02	0,95	0,13	-0,07
5	2,23%	27,13%	1,135	13,76	-7,67%	27,94%	1,15	13,76	-9,91%	1,8%	0,91	1,04	0,17	-0,14
Panel B - Idiosyncratic Skewness														
	In Sample Return Statistics					**Idiosyncratic**				**Beta**				
Quintile	**Mean**	**Vol**	**Skew**	**Kurtosis**	**RDV**	**Vol**	**Skew**	**Kurtosis**	**RDV**	**Alpha**	**Mkt**	**SMB**	**HML**	**MOM**
1	-0,80%	11,67%	-0,65	10,72	0,50%	10,79%	-0,74	11,06	-1,42%	-1,15%	0,79	0,53	0,13	-0,07
2	0,55%	12,24%	0,13	5,38	-0,59%	11,21%	0,13	5,12	0,60%	0,09%	0,85	0,58	0,19	-0,05
3	1,17%	14,20%	0,40	5,83	-1,89%	13,16%	0,43	5,59	1,85%	0,64%	0,92	0,72	0,20	-0,06
4	1,79%	16,14%	0,77	7,48	-4,05%	15,18%	0,83	7,37	3,59%	1,25%	0,93	0,83	0,20	-0,06
5	2,87%	19,11%	2,24	21,47	-11,48%	18,36%	2,33	21,91	8,73%	2,43%	0,79	0,80	0,18	-0,06
Panel C - Idiosyncratic Kurtosis														
	In Sample Return Statistics					**Idiosyncratic**				**Beta**				
Quintile	**Mean**	**Vol**	**Skew**	**Kurtosis**	**RDV**	**Vol**	**Skew**	**Kurtosis**	**RDV**	**Alpha**	**Mkt**	**SMB**	**HML**	**MOM**
1	1,11%	12,19%	0,17	4,02	-0,42%	11,02%	0,17	3,66	0,89%	0,66%	0,90	0,53	0,20	-0,04
2	1,17%	13,58%	0,29	5,05	-1,40%	12,53%	0,31	4,79	1,58%	0,65%	0,94	0,69	0,19	-0,05
3	1,11%	14,62%	0,43	6,43	-2,41%	13,68%	0,46	6,30	2,28%	0,60%	0,91	0,77	0,18	-0,06
4	1,01%	15,63%	0,62	9,18	-4,00%	14,79%	0,64	9,27	3,09%	0,54%	0,84	0,77	0,18	-0,08
5	1,23%	17,38%	1,40	26,07	-9,30%	16,69%	1,41	26,90	5,55%	0,86%	0,70	0,68	0,15	-0,08
Panel D - Idiosyncratic Relative Upside Volatility														
	In Sample Return Statistics					**Idiosyncratic**				**Beta**				
Quintile	**Mean**	**Vol**	**Skew**	**Kurtosis**	**RDV**	**Vol**	**Skew**	**Kurtosis**	**RDV**	**Alpha**	**Mkt**	**SMB**	**HML**	**MOM**
1	-1,07%	11,71%	-0,57	10,79	0,25%	10,85%	-0,66	11,08	-1,67%	-1,36%	0,76	0,50	0,14	-0,08
2	0,47%	9,62%	0,15	6,07	-0,53%	8,63%	0,16	5,78	0,43%	0,04%	0,79	0,46	0,20	-0,04
3	0,95%	12,01%	0,48	6,93	-1,60%	10,99%	0,53	6,77	1,45%	0,42%	0,90	0,66	0,21	-0,05
4	1,55%	15,58%	0,87	8,75	-3,49%	14,59%	0,93	8,83	3,13%	1,00%	0,96	0,86	0,19	-0,06
5	3,65%	24,37%	1,96	18,36	-12,13%	23,56%	2,02	18,62	9,99%	3,16%	0,88	0,97	0,17	-0,08

The idiosyncratic asymmetry measures Skewness and Relative Upside Volatility have a very high spread from high to low. The returns are strictly increasing from the first quintile up to the fifth quintile for both measures, for both weighting schemes and for all time-periods used. All the spreads are highly significant and ranging from 3,26% to 5,32%. On a monthly basis this is a very high and puzzling risk premium. The high spreads are mainly driven by the return in the fifth and first quintile while the other quintiles have returns of a more normal nature. In Table II we can note that both of these quintiles experience a very high idiosyncratic kurtosis which complicates the analysis in this

Table III - Single Sorted, t=0

In the below table the return for month t=0 are presented for each quintile when the stocks are single-sorted according to their idiosyncratic volatility, idiosyncratic skewness, idiosyncratic kurtosis and idiosyncratic relative downside volatility from low (1) to high (5). For each quintile the equally weighted return for each month is calculated and then the return is averaged across all months, these returns are presented in the columns to the left. The same procedure is done with value weighted returns and are represented in the columns to the right. The quintiles are rebalanced on a monthly basis. The spread is defined as 1-5 for idiosyncratic volatility and kurtosis and 5-1 for idiosyncratic asymmetry measures. The t-statistics is with respect to the spread-portfolioas with the null-hypothesis that the return for the portfolio is equal to 0. Panel A presents the result for the full sample period 1966-2011, Panel B presents the sub-sample 1966-1989 and Panel C presents the sub-sample 1990-2011.

	Volatility		**Skewness**		**Kurtosis**		**RU Volatility**	
Quintile	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**
Panel A :Full Sample								
1	0,50%	0,70%	-1,53%	-0,78%	0,57%	0,89%	-1,83%	-0,90%
2	0,70%	0,81%	0,04%	0,53%	0,60%	0,73%	0,19%	0,74%
3	0,74%	1,01%	0,65%	1,00%	0,61%	0,82%	0,66%	1,13%
4	0,55%	0,90%	1,41%	1,62%	0,63%	0,80%	1,23%	1,63%
5	1,16%	1,36%	3,04%	2,86%	1,25%	1,26%	3,34%	3,57%
Spread	-0,66%	-0,66%	4,57%	3,65%	-0,68%	-0,37%	5,17%	4,47%
(t)	-0,64	-1,43	**12,20**	**10,39**	**-1,98**	-1,09	**11,91**	**9,92**
Panel B: 1966-1989								
1	0,48%	0,66%	-1,46%	-0,68%	0,50%	0,74%	-1,83%	-0,82%
2	0,68%	0,85%	0,11%	0,61%	0,55%	0,63%	0,20%	0,80%
3	0,69%	1,00%	0,71%	0,96%	0,56%	0,76%	0,65%	1,18%
4	0,55%	0,95%	1,36%	1,63%	0,53%	0,83%	1,18%	1,65%
5	1,04%	1,53%	2,68%	2,58%	1,19%	1,01%	3,20%	3,39%
Spread	-0,56%	-0,87%	4,14%	3,26%	-0,68%	-0,28%	5,03%	4,21%
(t)	-1,02	-1,43	**8,16**	**6,94**	-1,39	-0,62	**8,70**	**7,33**
Panel C: 1990-2011								
1	0,52%	0,74%	-1,60%	-0,89%	0,64%	1,06%	-1,83%	-0,99%
2	0,73%	0,77%	-0,03%	0,46%	0,66%	0,83%	0,19%	0,69%
3	0,78%	1,02%	0,58%	1,04%	0,66%	0,88%	0,67%	1,07%
4	0,56%	0,84%	1,46%	1,60%	0,73%	0,76%	1,29%	1,60%
5	1,28%	1,17%	3,43%	3,16%	1,32%	1,53%	3,50%	3,76%
Spread	-0,76%	-0,43%	5,03%	4,06%	-0,68%	-0,47%	5,32%	4,75%
(t)	-1,38	-0,62	**9,08**	**7,73**	-1,40	-0,91	**8,16**	**6,78**

trivial single sorting setting. The monotonic pattern does suggest that idiosyncratic skewness have a high positive correlation with returns and plays a crucial part in determining the realized return. The similar results for both weighting schemes suggest that the market value does not infer with results within the quintiles. Idiosyncratic kurtosis also has higher average return in the highest quintile. No pattern cannot be detected in the other four quintiles for neither equally-weighted returns or value-weighted returns. Given the data description there seems to be a strong correlation between absolute asymmetry and kurtosis and the individual effect are therefore difficult to separate, as noted above.

Hence the variables have to be simultaneously controlled for to draw any definite conclusions. Both in this contemporaneous setting and in the out-of-sample setting do idiosyncratic volatility display a completely different behavior compared to the expected return setting of Ang et al (2006 & 2009). In contrast my results show that high idiosyncratic volatility has a higher average return than quintiles with lower idiosyncratic volatility.

There is nonetheless no real significance and the patterns for the other four quintiles are in no way strict. Since the estimation period used differ a lot from their papers as well as the inclusion of the momentum factor in the regressions this solidifies the results of Bali and Cekici (2008) who find that the relationship between idiosyncratic volatility and returns is highly sensitive to different empirical procedures.

Table IV - Single Sorted, t=1

In the below table the return for month t=1 are presented for each quintile when the stocks are single-sorted according to their idiosyncratic volatility, idiosyncratic skewness, idiosyncratic kurtosis and idiosyncratic relative downside volatility from low (1) to high (5). For each quintile the equally weighted return for each month is calculated and then the return is averaged across all months, these returns are presented in the columns to the left. The same procedure is done with value weighted returns and are represented in the columns to the right. The quintiles are rebalanced on a monthly basis. The spread is defined as 1-5 for idiosyncratic volatility and kurtosis and 5-1 for the idiosyncratic asymmetry measures. The t-statistics is with respect to the spread-portfolioas with the null-hypothesis that the return for the portfolio is equal to 0. Panel A presents the result for the full sample period 1966-2011.

Panel A :Full Sample

	Volatility			**Skewness**			**Kurtosis**			**RU Volatility**	
Quintile	**EW**	**VW**		**EW**	**VW**		**EW**	**VW**		**EW**	**VW**
1	0,61%	0,55%		0,60%	0,53%		0,74%	0,58%		0,65%	0,65%
2	0,80%	0,68%		0,74%	0,60%		0,77%	0,59%		0,69%	0,60%
3	0,82%	0,81%		0,79%	0,65%		0,76%	0,65%		0,80%	0,74%
4	0,68%	0,55%		0,85%	0,64%		0,72%	0,87%		0,88%	0,79%
5	0,88%	0,65%		0,82%	0,88%		0,80%	0,80%		0,77%	0,85%
Spread	-0,27%	-0,10%		0,22%	0,36%		-0,07%	-0,22%		0,11%	0,20%
(t)	-0,63	-0,23		0,62	1,04		-0,19	-0,70		0,27	0,47

The idiosyncratic asymmetry measures as well as idiosyncratic kurtosis does not show any sign of having predictive power. There is some positive relationship between all variables and the average return but they are far from being significant. Idiosyncratic skewness with value-weighted returns is the only measure that have a strictly increasing return from low to high, but the spread is only 0,36% with a t-stat of 1,04.

2.3.2 Single Sorting within Risk Factors

The results when controlling for idiosyncratic volatility are displayed in Table V. A monotonic pattern can be observed for idiosyncratic skewness within all 5 quintiles of idiosyncratic volatility, where the returns are increasing from the first skewness quintile up to the fifth. The fifth quintile does however not manage to produce homogenous idiosyncratic volatilities and does not have the same relevance as the other quintiles where the average idiosyncratic volatility measures are equal regardless of idiosyncratic skewness quintile (see Table A in Appendix for descriptive statistics of the different portfolios). The same pattern as for idiosyncratic skewness is also present for idiosyncratic relative upside volatility and the results are robust to weighting scheme. The increases are of greater magnitude and significance in the higher idiosyncratic volatility quintiles. This make the results in A. more robust and continue to suggest that idiosyncratic asymmetry is indeed priced.

The returns sorted on idiosyncratic kurtosis does once again not reveal any unambiguous patterns when equally weighting the returns. The behavior in the fifth idiosyncratic volatility -quintile does however show some consistent pattern where the returns increase continuously from the first idiosyncratic kurtosis quintile up until the fifth but showcasing an unsignificant spread. There is also a difference between the equally weighted and value weighted procedures. For the first four quintiles the pattern is clear with increasing returns from high idiosyncratic kurtosis quintiles to the low quintiles (negative correlation between returns and idiosyncratic kurtosis) when the returns are value-weighted instead of equally weighted. This result seem likely if we expect the puzzling effect that the most preferred quintile also have highest returns (as in Ang et. Al, 2006) and take into account that preferences for retail investor is more present with equally weighted returns. Since retail investors often stay undiversified and have a higher portion of their wealth in small stocks than professional investors and have lottery-like preferences as opposed to institutions this could explain the reversed effect when changing weighting procedure. Even though the reversed pattern is interesting the spreads within the weighting schemes are far from significant.

Table V - Contemperaneous Return, Single Sorted within Idiosyncratic Volatility

In Table V the returns are presented when stocks first are sorted into quintiles with respect to their Idiosyncratic Volatility. Then a sorting procedure within the quintiles are performed: for Idiosyncratic Skewness, Idiosyncratic Kurtosis and Idiosyncratic Relative Upside Volatility from low (1) to high (5). The returns are calculated by averaging the returns for each month and then taking the average across all 541 months. The 25 portfolios are rebalanced on a monthly basis. Panel A presents the full sample for t=0 and Panel B presents the full sample for t=1, these panels represent equally weighted averages. Panel C presents the full sample for t=0 and Panel D presents the full sample for t=1, these panels represent value weighted averages. The spreads for Idiosyncratic Skewness and Idiosyncratic Upside Volatility are defined as 5-1. The spread for Idiosyncratic Kurtosis is defined as the 1-5. T-stats for the spreads are presented below.

Panel A: Full Sample, t=0, EW

Idiosyncratic Volatility	Idiosyncratic Skewness						Idiosyncratic Kurtosis						Idiosyncratic Relative Upside Volatility					
	1	2	3	4	5	Spread	1	2	3	4	5	Spread	1	2	3	4	5	Spread
1	-0,44%	0,27%	0,52%	0,82%	1,31%	1,76%	0,49%	0,53%	0,53%	0,50%	0,44%	0,05%	-0,53%	0,21%	0,50%	0,80%	1,52%	2,05%
						9,11						0,24						**10,21**
2	-0,86%	0,32%	0,82%	1,27%	1,96%	2,82%	0,68%	0,67%	0,74%	0,75%	0,66%	0,02%	-1,02%	0,29%	0,73%	1,24%	2,28%	3,30%
						10,31						0,07						**11,95**
3	-1,57%	0,22%	0,90%	1,57%	2,57%	4,14%	0,76%	0,75%	0,75%	0,67%	0,75%	0,02%	-1,78%	0,13%	0,80%	1,50%	3,02%	4,80%
						11,79						0,05						**13,51**
4	-2,39%	-0,18%	0,69%	1,66%	2,99%	5,39%	0,58%	0,49%	0,50%	0,43%	0,77%	-0,20%	-2,76%	-0,31%	0,61%	1,59%	3,64%	6,40%
						12,30						-0,46						**14,34**
5	-2,91%	-0,04%	1,16%	2,39%	5,20%	8,11%	0,37%	0,45%	0,75%	1,11%	3,13%	-2,76%	-3,56%	-0,37%	1,04%	2,46%	6,23%	9,78%
						13,32						**-4,73**						**15,21**

Panel B: Full Sample, t=1, EW

Idiosyncratic Volatility	Idiosyncratic Skewness						Idiosyncratic Kurtosis						Idiosyncratic Relative Upside Volatility					
	1	2	3	4	5	Spread	1	2	3	4	5	Spread	1	2	3	4	5	Spread
1	0,47%	0,54%	0,60%	0,71%	0,75%	0,28%	0,50%	0,59%	0,68%	0,70%	0,61%	-0,11%	0,45%	0,52%	0,60%	0,66%	0,83%	0,38%
						1,42						-0,55						1,82
2	0,61%	0,73%	0,83%	0,94%	0,91%	0,30%	0,78%	0,79%	0,84%	0,87%	0,74%	0,03%	0,60%	0,73%	0,81%	0,92%	0,96%	0,37%
						1,09						0,12						1,33
3	0,57%	0,77%	0,86%	0,95%	0,93%	0,36%	0,85%	0,83%	0,85%	0,79%	0,76%	0,09%	0,58%	0,76%	0,81%	0,97%	0,96%	0,38%
						1,05						0,27						1,09
4	0,65%	0,66%	0,71%	0,65%	0,72%	0,07%	0,81%	0,72%	0,64%	0,47%	0,75%	0,07%	0,71%	0,65%	0,65%	0,66%	0,71%	0,00%
						0,16						0,16						0,00
5	1,31%	0,90%	0,86%	0,65%	0,67%	-0,64%	1,01%	0,80%	0,81%	0,74%	1,03%	-0,02%	1,48%	0,88%	0,72%	0,70%	0,62%	-0,86%
						-1,12						-0,04						-1,46

Panel C: Full Sample, t = 0 VW

Idiosyncratic Volatility	Idiosyncratic Skewness						Idiosyncratic Kurtosis						Idiosyncratic Relative Upside Volatility					
	1	2	3	4	5	Spread	1	2	3	4	5	Spread	1	2	3	4	5	Spread
1	-0,02%	0,57%	0,85%	1,28%	1,46%	1,49%	0,84%	0,77%	0,73%	0,82%	0,52%	0,31%	-0,11%	0,51%	0,87%	1,27%	1,61%	1,72%
						6,34						1,31						**7,05**
2	-0,32%	0,82%	1,32%	1,73%	2,17%	2,48%	1,10%	1,07%	1,12%	0,96%	0,78%	0,32%	-0,45%	0,84%	1,17%	1,68%	2,57%	3,02%
						8,10						1,02						**9,66**
3	-0,45%	1,01%	1,66%	2,42%	3,09%	3,53%	1,58%	1,64%	1,36%	1,24%	1,17%	0,41%	-0,66%	1,06%	1,52%	2,29%	3,50%	4,16%
						8,81						1,00						**10,34**
4	-1,07%	1,11%	1,88%	2,71%	3,59%	4,65%	1,93%	1,79%	1,70%	1,42%	1,17%	0,76%	-1,38%	1,07%	1,56%	2,38%	4,11%	5,49%
						9,20						1,44						**10,91**
5	-2,44%	1,10%	2,06%	3,31%	6,23%	8,67%	1,28%	1,63%	1,76%	1,77%	3,97%	-2,68%	-3,07%	0,45%	2,17%	3,89%	7,45%	10,51%
						12,35						**-4,02**						**13,83**

Panel D: Full Sample, t=1, VW

Idiosyncratic Volatility	Idiosyncratic Skewness						Idiosyncratic Kurtosis						Idiosyncratic Relative Upside Volatility					
	1	2	3	4	5	Spread	1	2	3	4	5	Spread	1	2	3	4	5	Spread
1	0,56%	0,49%	0,54%	0,67%	0,58%	0,02%	0,52%	0,46%	0,51%	0,58%	0,46%	0,07%	0,58%	0,51%	0,55%	0,60%	0,70%	0,12%
						0,10						0,28						0,52
2	0,49%	0,52%	0,63%	0,62%	0,79%	0,30%	0,56%	0,58%	0,45%	0,61%	0,77%	-0,22%	0,45%	0,56%	0,58%	0,70%	1,00%	0,55%
						0,99						-0,69						1,78
3	0,37%	0,59%	0,57%	0,83%	0,86%	0,49%	0,55%	0,64%	0,47%	0,54%	0,81%	-0,27%	0,48%	0,58%	0,53%	0,84%	1,00%	0,52%
						1,28						-0,68						1,33
4	0,46%	0,36%	0,20%	0,59%	0,95%	0,49%	0,58%	0,39%	0,31%	0,33%	0,62%	-0,04%	0,60%	0,39%	0,45%	0,43%	0,83%	0,23%
						1,00						-0,08						0,47
5	1,24%	0,63%	0,55%	0,20%	0,52%	-0,73%	0,62%	0,48%	0,63%	0,53%	0,82%	-0,19%	1,36%	0,81%	0,12%	0,59%	0,20%	-1,16%
						-1,18						-0,30						-1,78

For the out-of-sample results for idiosyncratic asymmetry the return increases for each of the first three quintiles with the positive asymmetry, then turning insignificant and for the fifth quintile the spread is negative. Meaning that stocks with low idiosyncratic skewness and idiosyncratic upside volatility have higher returns than their first quintile counterparties. This is a complete reversal compared not only to the returns for month *t=0* but also compared to the case when idiosyncratic volatility is not controlled for (which it can be argued is not the case here either since the variable still has a lot of dispersion in the fifth quintile). The portfolio of high idiosyncratic volatility and low idiosyncratic skewness had a return of -2,91% for month *t*=0 which for the first out-of-sample month is 1,31%. This return reversal effect have previously been documented by Huang, Liu, Rhee and Zhang (2010) which according to them drives the negative price of idiosyncratic volatility risk. We also know that the autoregressive coefficient for skewness is negative, this could explain the overall pattern where the idiosyncratic asymmetry shows signs of being priced contemporaneously whilst the spread significantly decreases one month ahead. The idiosyncratic kurtosis returns does not show any clear and unambiguous patterns.

Literature have documented that illiquid and small firms usually experience a high degree of positive skewness. With the risk factors as portfolios largely having negative skewness, they could have a hard time pricing small and illiquid stocks which hence would show up in the errors. Therefore the idiosyncratic skewness is also analyzed within size and illiquidity quintiles to control for their effects. As can be observed in Table VI, Idiosyncratic Skewness and its returns spread from high to low is robust to the effects of illiquidity and size. The same monotonic pattern from low to high is once again present. When controlling for Market Value it seems the spread becomes less significant for the quintiles with stocks with higher market value, the spread in the fifth quintile is 3,15% whilst it is 6,39% for first. This suggest that small stocks in part drives the results, even if it is far from the only explanation since the quintile with large stocks still has a very significant return spread for high idiosyncratic skewness to low.

There is some difference between the quintiles sorted on Illiq as well, the spread is higher for very liquid stocks than for illiquid stocks (those in the highest Illiq quintile). The same monotonic pattern can however be recognized in all quintiles at the same time all the spreads are significant.

Table VI - Idiosyncratic Skewness Sorting within MV & Illiq quintiles

In Table VI the returns for t=0 are presented when stocks first are sorted into quintiles with respect to their Market Value (left column) and the illiquidity variable Illiq (right column), developed by Amihud (2003). Then a sorting procedure within the quintiles are performed for Idiosyncratic Skewness. The returns are calculated by averaging the returns (equally-weighted) for each month and then taking the average across all 541 months. The 25 portfolios are rebalanced on a monthly basis. T-stats for the spreads are presented below.

Panel A: Full Sample

		Idiosyncratic Skewness								**Idiosyncratic Skewness**					
		1	2	3	4	5	Spread			1	2	3	4	5	Spread
Market Value	1	-4,11%	-1,99%	-1,15%	0,07%	2,27%	6,39%	**Illiq**	1	-0,91%	0,71%	1,49%	2,43%	4,45%	5,35%
							14,33								**12,43**
	2	-2,04%	-0,14%	0,66%	1,68%	3,77%	5,81%		2	-1,17%	0,46%	1,19%	2,07%	4,01%	5,18%
							13,82								**11,65**
	3	-1,37%	0,26%	1,12%	2,08%	3,84%	5,21%		3	-1,61%	0,00%	0,67%	1,55%	3,60%	5,21%
							13,04								**12,52**
	4	-0,75%	0,56%	1,19%	2,00%	3,60%	4,34%		4	-1,85%	-0,49%	0,17%	0,96%	3,11%	4,96%
							11,51								**12,67**
	5	-0,25%	0,64%	1,15%	1,71%	2,90%	3,15%		5	-2,45%	-0,92%	-0,83%	0,11%	2,02%	4,47%
							9,63								**9,57**

2.3.3 Double Sorting

Given the strong relationship between skewness and kurtosis they can be troublesome to analyze separately. Therefore the double-sorting procedure, found in Fama-French (1993) among other papers, is ideal to separate the two risks from each other. The results are displayed in Table VI below. The double-sorting procedure will hopefully be able to separate the risks of both measures.

The documented positive relationship between Idiosyncratic Asymmetry and average returns in A. and B. holds when double-sorting the stocks together with idiosyncratic kurtosis as well. The pattern is monotonic for both asymmetry measures as well as both weighting procedures. The spread are smaller than in previous methods but still very high and economically and statistically significant. When equally weighted averages are used the spread from high idiosyncratic skewness to low is estimated as 3,8% and with value weighted averages it is 2,98%. The estimates have t-stats of 9,83 and 8,88 respectively. When idiosyncratic relative upside volatility is used as a measure for the asymmetry the risk premiums are 3,75% and 3,44% with t-stats of 10,18 and 8,63.

Table VII

In the below table the results from the Double-Sorting procedure are presented. Stocks are sorted both on idiosyncratic asymmetry (both measurs) and idiosyncratic kurtosis and then placed into portfolio according to the intersections. The returns are first averaged across all observations for each month and then averaged across all months of the sample. Panel A displays the results with equally weigted averages and Panel B displays value weighted averages. The spread portfolios are for Idiosyncratic Volatility defined as the average return for the first tercile minus the average return for the fifth tercile. The reverse is the definition for the idiosyncratic asymmetry spread-portfolios. T-stats for the spread portfolios are also presented.

Panel A - EW

		Idiosyncratic Kurtosis				
Idiosyncratic Skewness	Terciles	**1**	**2**	**3**	***is - HML***	***ik - LMH***
	1	-0,08%	-1,13%	-2,33%	3,80%	1,24%
	2	1,00%	0,56%	-0,38%	**9,83**	**3,39**
	3	2,81%	2,34%	2,72%		

		Idiosyncratic Kurtosis				
Idiosyncratic Relative Upside Volatility	Terciles	**1**	**2**	**3**	***iruv - HML***	***ik - LMH***
	1	-0,04%	-1,28%	-2,69%	3,75%	0,53%
	2	0,87%	0,66%	0,32%	**10,18**	1,55
	3	1,73%	2,17%	3,35%		

Panel B - VW

		Idiosyncratic Kurtosis				
Idiosyncratic Skewness	Terciles	**1**	**2**	**3**	***is - HML***	***ik - LMH***
	1	0,48%	-0,18%	-1,55%	2,98%	0,99%
	2	1,31%	1,02%	0,62%	**8,88**	**2,98**
	3	2,79%	2,37%	2,54%		

		Idiosyncratic Kurtosis				
Idiosyncratic Relative Upside Volatility	Terciles	**1**	**2**	**3**	***iruv - HML***	***ik - LMH***
	1	0,53%	-0,16%	-1,72%	3,44%	0,65%
	2	1,34%	1,11%	1,00%	**8,63**	1,90
	3	2,87%	2,58%	3,51%		

In this setting idiosyncratic kurtosis show some signs of being priced. Moreover this only holds when paired with idiosyncratic skewness, then it commands a risk premium of 1,24% (0,99%) when returns are equally (value) weighted. This suggest that some of the correlation between idiosyncratic asymmetry and kurtosis drives idiosyncratic kurtosis to have a positive relationship with returns which disappears when controlling for the asymmetry. When double-sorting with respect to idiosyncratic asymmetry and volatility at the same time the idiosyncratic asymmetry commands a risk premium ranging from 3,44 to 4,63%.

Table VIII

In the below table the results from the Double-Sorting procedur are presented. Stocks are sorted both on idiosyncratic volatility and idiosyncratic asymmetry (both measures) and then placed into portfolio according to the intersections. The returns are first averaged across all observations for each month and then averaged across all months of the sample. Panel A displays the results with equally weigted averages and Panel B displays value weighted averages. The spread portfolios are for Idiosyncratic Volatility defined as the average return for the first tercile minus the average return for the fifth tercile. The reverse is the definition for the idiosyncratic asymmetry spread-portfolios. T-stats for the spread portfolios are also presented.

Panel A - EW

		Idiosyncratic Skewness				
	Terciles	**1**	**2**	**3**	***iv - LMH***	***is- HML***
Idiosyncratic Volatility	**1**	-0,10%	0,82%	1,60%	0,74%	3,77%
	2	-1,05%	0,89%	2,34%	1,83	**10,68**
	3	-3,13%	0,14%	3,10%		
		Idiosyncratic Relative Upside Volatility				
	Terciles	**1**	**2**	**3**	***iv - LMH***	***iruv- HML***
	1	-0,09%	1,07%	2,79%	2,05%	4,63%
	2	-1,33%	0,84%	2,82%	**5,19**	**13,07**
	3	-4,23%	-0,79%	2,63%		

Panel B - VW

		Idiosyncratic Skewness				
	Terciles	**1**	**2**	**3**	***iv - LMH***	***is- HML***
Idiosyncratic Volatility	**1**	0,29%	1,09%	1,71%	0,58%	3,44%
	2	-0,30%	1,35%	2,57%	1,39	**9,59**
	3	-2,70%	0,73%	3,33%		
		Idiosyncratic Relative Upside Volatility				
	Terciles	**1**	**2**	**3**	***iv - LMH***	***iruv- HML***
	1	0,34%	1,27%	2,84%	1,51%	4,08%
	2	-1,33%	0,84%	2,82%	**3,55**	**10,92**
	3	-3,29%	0,31%	2,89%		

The results are specifically significant when the asymmetry measure idiosyncratic upside volatility is used. This measure also seems more robust to the effect of idiosyncratic volatility since the high idiosyncratic relative upside volatility terciles have very similar returns whilst the idiosyncratic skewness and its high terciles are much more dependent on which return of the idiosyncratic volatility terciles that is scrutinized. We can also note that idiosyncratic volatility spread from low to high is significant when controlling for relative upside volatility, then the low portfolios have a spread over the high portfolios in the equally weighted (value weighted) case of 2,05% (1,51%) with a t-stat of 5,19 (3,55). This could be due to the fact that the measurement of idiosyncratic volatility is too noisy when single sorting and its correlation with the asymmetry measures underestimate its true effect on returns. The asymmetry measure of idiosyncratic risk continues to be significantly priced with a clear monotonic pattern.

All the tests suggest that idiosyncratic asymmetry is priced. None of the controls or different weighting schemes changes the monotonic pattern of stocks with low idiosyncratic asymmetry having a low return and the return increasing with the estimate of idiosyncratic asymmetry. The robustness tests suggests that small stocks bias the overall estimated spread a bit upwards but the spread and monotonic pattern found are still significant for stocks with high market value. The spreads are relatively high compared to the t-stats meaning that the relationship between idiosyncratic skewness and returns varies a lot and the significance is more driven by the nominator. The different risk measures also seem to co-vary pretty strongly. When this is controlled for idiosyncratic volatility and kurtosis also seem to have a spread in some of the settings, but these results are not robust to which of the asymmetric asymmetry measures that are used.

These results can have a number of different explanations. If negative co-skewness with market would indicate high idiosyncratic skewness (in a two moment model) the sign of the spread would not be puzzling. To experience higher returns in market downturns a portfolio would have to have positive co-skewness with respect to the market. This would be desirable, leading to negative co-skewness demanding a risk premium and on average experiencing high returns due to the inability to act as a hedge in downturns. This relationship is however not analyzed. The sign of the results seem to be in line with, even though not directly comparable, Boyd, Mitton, Vorkink (2009) that find a negative relationship between expected idiosyncratic skewness and average returns. Harvey and Siddique (1999) find that the autoregressive parameter for monthly skewness is -0.4. This could explain the fact that the spread found for t=0 is significant but vanishes in t=1. I.e. a high estimate of idiosyncratic skewness for *t=0* would, through the negative autoregressive coefficient, have had a negative impact on the expected idiosyncratic skewness for t=1.

Another explanation could be that the model does not capture risk associated with small firms, value stocks, firms with high leverage and poor credit ratings. These stocks generally have high skewness and if the risk factor portfolios used are bad proxies that does not capture the risk, their skewness would be found in the errors. The fact that small stocks seem to explain some portion of the high spread, while SMB betas does not differ across idiosyncratic skewness, suggests that this could be a possible explanation. A third explanation could be that the idiosyncratic asymmetry is highly correlated with some omitted risk factor which drives the high spreads observed in all sorting procedures.

The results for idiosyncratic volatility and kurtosis are not conclusive which is in contrast to Ang et al (2006) that find idiosyncratic volatility being negatively correlated with future expected returns. The procedure does however vary and this would suggest that Bali and Cakici (2008) could be right in their critique that the risk premium associated with idiosyncratic volatility is very sensitive to the empirical framework.

The findings also suggests that the two-moment asset pricing model fail to price higher order moments, given the magnitude of idiosyncratic higher order moments and the fact that they are priced. This points towards a need for more easily manageable asset pricing models with more than two moments who can handle the pricing of co-skewness and co-kurtosis. Such models could also more easily handle other types of instruments such as options which have high skewness and kurtosis exposure by construction as well as bonds which with their finite horizons have a time-dependency that results in more positively skewed returns. The inability of the standard models to price higher order moments and the fact that the stock market have a negative skewness while bonds typically have positive skewness would also mitigate the equity premium puzzle since part of the stock markets return would come from a negative skewness premium which would decrease the required risk aversion coefficient to explain the performance difference between stocks and bonds.

2.4 Conclusion

The results of a strong relationship between idiosyncratic asymmetry and average returns with low idiosyncratic skewness portfolios having low returns and high idiosyncratic skewness portfolios have high returns with a strictly monotonic pattern in between indicates that idiosyncratic asymmetry is priced contemporaneously in the cross-section of stock returns. The idiosyncratic asymmetry does not have any predictive power for future expected returns. The result persists when controlling for the impact of idiosyncratic volatility, market value and liquidity. They are also robust when separating the risks of the idiosyncratic asymmetry from idiosyncratic volatility and kurtosis. In the double-sorting framework the latter two variables seems to have a negative relationship with average returns, which is not present in the first sorting procedures. This underlines the difficulty of getting results related to idiosyncratic risk that are not highly sensitive to modifications of the empirical framework. Using the ICAPM theoretical framework together with behavioral evidence about investors preferences for the moments of return distributions these results are puzzling. I do not empirically try to explain the results but a set of different explanations can be tested. An analysis of idiosyncratic higher order moments when the asset pricing model used incorporates co-skewness and co-kurtosis is one possible extension that could be made. Although a number of robustness checks were performed there is still room for more. A modification of the benchmark regression model is one, an analysis of the results robustness to different market conditions is another and controlling for a larger set of previously documented risk factors within the used sorting procedure is a third.

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2.5.2 Data

All stock price data is taken from WRDS's CRSP library. All the factor portfolios and the risk-free rate are taken from the Fama-French Data Library (through WRDS).

2.6 Appendix

Table A - Descriptives for Idiosyncratic Skewness sorted quintiles within Idiosyncratic Volatility quintiles

The table below presents descriptives for Idiosyncratic Skewness sorting within Idiosyncratic Volatility quintiles. The first two columns presents which quintile that are presented on that row. Columns 3-7 presents in sample statistics, columns 8-11 presents statistics for the residuals of the regressions and columns 12-16 presents estimatd parameters from the regressions. All values are equally weighted for each regressions period and then averaged across each of the 541 months. The alphas, mean and volatilities are monthly scaled.

		In-Sample					Idiosyncratic					Beta			
iv	*is*	**Mean**	**Volatility**	**Skewness**	**Kurtosis**	**RDV**	**Vol**	**Skew**	**Kurtosis**	**RUV**	**Alpha**	**Mkt**	**SMB**	**HML**	**Mom**
1	1	-0,11%	5,7%	-0,80	11,13	0,4%	5,1%	-0,83	10,78	-0,9%	-0,41%	0,51	0,18	0,18	-0,02
1	2	0,42%	5,9%	-0,06	5,34	0,1%	5,1%	-0,06	4,83	0,0%	0,09%	0,60	0,18	0,20	-0,01
1	3	0,60%	6,1%	0,15	5,48	-0,3%	5,2%	0,19	4,93	0,4%	0,24%	0,64	0,21	0,21	-0,02
1	4	0,79%	6,2%	0,41	6,72	-0,8%	5,3%	0,49	6,23	0,8%	0,41%	0,63	0,26	0,22	-0,01
1	5	1,08%	6,0%	1,54	16,32	-2,5%	5,3%	1,66	16,23	2,0%	0,79%	0,50	0,26	0,19	-0,02
2	1	-0,32%	9,2%	-0,64	9,91	0,6%	8,3%	-0,75	10,45	-1,2%	-0,71%	0,79	0,42	0,18	-0,06
2	2	0,61%	9,3%	0,06	5,20	-0,2%	8,3%	0,05	4,93	0,2%	0,16%	0,85	0,46	0,21	-0,03
2	3	0,95%	9,4%	0,28	5,42	-0,9%	8,3%	0,31	5,11	0,9%	0,45%	0,89	0,52	0,24	-0,03
2	4	1,25%	9,3%	0,55	6,56	-1,7%	8,4%	0,64	6,36	1,6%	0,76%	0,87	0,56	0,24	-0,02
2	5	1,62%	9,2%	1,64	16,00	-4,0%	8,4%	1,80	16,60	3,2%	1,23%	0,70	0,51	0,21	-0,02
3	1	-0,71%	12,6%	-0,64	10,71	0,5%	11,6%	-0,76	11,44	-1,5%	-1,18%	0,94	0,68	0,12	-0,07
3	2	0,69%	12,7%	0,15	5,30	-0,7%	11,6%	0,14	5,16	0,6%	0,19%	0,98	0,72	0,17	-0,04
3	3	1,23%	12,8%	0,39	5,67	-1,6%	11,6%	0,43	5,49	1,6%	0,67%	1,02	0,78	0,19	-0,03
3	4	1,65%	12,7%	0,70	7,00	-2,8%	11,7%	0,77	6,94	2,6%	1,07%	1,01	0,82	0,21	-0,03
3	5	2,08%	12,5%	1,88	17,81	-6,0%	11,7%	2,03	18,67	4,7%	1,63%	0,83	0,72	0,22	-0,03
4	1	-1,36%	17,1%	-0,64	11,55	0,4%	15,9%	-0,75	12,31	-1,8%	-1,82%	1,01	0,89	0,04	-0,11
4	2	0,60%	17,1%	0,25	5,57	-1,4%	16,0%	0,24	5,48	1,3%	0,08%	1,03	0,93	0,14	-0,08
4	3	1,32%	17,2%	0,52	6,04	-2,9%	16,1%	0,54	5,91	2,7%	0,74%	1,07	0,99	0,15	-0,06
4	4	1,84%	17,2%	0,86	7,63	-4,6%	16,1%	0,91	7,61	4,1%	1,24%	1,07	1,01	0,16	-0,06
4	5	2,48%	17,1%	2,18	20,58	-9,5%	16,2%	2,29	21,30	7,1%	1,99%	0,90	0,90	0,17	-0,06
5	1	-1,19%	25,4%	-0,33	10,46	-0,7%	24,6%	-0,39	10,70	-0,6%	-1,61%	0,91	1,01	0,14	-0,21
5	2	1,52%	26,6%	0,49	6,05	-3,9%	25,8%	0,47	5,90	3,9%	1,04%	0,92	1,04	0,20	-0,16
5	3	2,54%	27,6%	0,83	7,33	-7,1%	26,8%	0,83	7,19	6,4%	2,02%	0,95	1,08	0,20	-0,13
5	4	3,34%	28,7%	1,34	10,63	-11,8%	27,9%	1,35	10,56	9,6%	2,82%	0,94	1,09	0,17	-0,13
5	5	5,03%	31,9%	3,40	34,34	-26,2%	31,2%	3,41	34,46	19,1%	4,58%	0,81	0,99	0,16	-0,09