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Growth Expectations, Dispersion of Beliefs and the Cross-Section of Stock Returns

by

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Abstract

The present study investigates whether the mean and the standard deviation of real GDP growth forecasts from the ECB Survey of Professional Forecasters (SPF) can help to explain the cross-sectional variation of expected returns in the German stock market. The expected real GDP growth from the SPF can be interpreted as a proxy for expected business conditions, whereas the cross-sectional dispersion of these expectations may serve as a proxy for macroeconomic uncertainty. I find support for the hypothesis that growth expectations and macroeconomic uncertainty are highly correlated and hence should be measured simultaneously to circumvent a potential omitted variable bias. The overall results of my asset-pricing tests provide more evidence for a premium associated with expected real GDP growth than for a premium on the macroeconomic uncertainty factor, however, the results are to some extent contradicting and might be influenced by multicollinearity.

Keywords: Growth expectations, dispersion of beliefs, macroeconomic uncertainty, cross-section of stock returns, omitted variable bias, multicollinearity.

Table of Contents

List of Tables

List of Figures

1 Introduction

Following the cross-sectional regression approach introduced by Fama and MacBeth (1973), several studies find that, against the implication of the capital asset pricing model (CAPM), market beta has little power in explaining the cross-sectional variation of expected stock returns. The central question that arises from this implication is what alternative factors could drive average stock returns. One common approach is to link average stock returns to macroeconomic fundamentals. Chen et al. (1986) and Fama and French (1989), for example, argue that there exists a relation between expected business conditions and expected returns. However, their suggested standard predictors dividend yield, default premium and term premium are not macroeconomic variables, but rather financial, as claimed by Campbell and Diebold (2009). Fama and French (1989) suggest that the explanatory power of the standard financial predictors may come from the potential ability of those variables to serve as proxies for expected business conditions, while Campbell and Diebold (2009) show that this claimed relation is subject to a lot of noise and conclude that a direct measure of expected business conditions might improve return predictions.

However, few attempts have yet been made to use direct measures of macroeconomic expectations for cross-sectional asset-pricing tests. Goetzmann et al. (2012), for example, find that expected real Gross Domestic Product (GDP) growth has significant power in explaining the cross-sectional variation in stock returns in the U.S. stock market. In particular, they find that stocks whose returns comove with expected real GDP growth earn higher returns than countercyclical stocks. They motivate this relation with the intuition already stated by Cochrane (1999), that procyclical stocks offer less protection against a decline in wealth during recessions, and therefore have to offer higher average returns in equilibrium to compensate investors for the additional source of risk.

In my essay, I build upon those inferences and investigate whether a model that simultaneously contains the mean and the standard deviation of real GDP growth expectations from the European Central Bank (ECB) Survey of Professional Forecasters (SPF) can help to explain the cross-sectional variation in expected returns in the German stock market. However, the main contribution of my study is that my suggested model not only includes a direct measure of macroeconomic expectations, but also considers the dispersion of those expectations as an additional factor to explain the cross-section of stock returns. In particular, the expected real GDP growth from the SPF can be interpreted as a proxy for expected business conditions, whereas the dispersion of these expectations may serve as a proxy for macroeconomic uncertainty. Lee and Kim (2014) and Bali et al. (2014) both suggest that stocks that earn low returns under high dispersion of beliefs expose investors to additional risk and are therefore unattractive to risk-averse investors. Consequently, stocks whose returns correlate less with dispersion of beliefs should provide higher average returns, to be held in equilibrium.

The motivation for including both factors in one model particularly comes from the omitted variable bias I suspect to be inherent in previous studies. Given the reasonable assumption that expected business conditions are negatively correlated with macroeconomic uncertainty (see for example Sepulveda-Umanzor 2004), some of the explanatory power of the expected GDP growth rates in previous studies might be actually due to changes in macroeconomic uncertainty. That is, a decrease in growth expectations might be driven by higher uncertainty rather than a changed growth assessment. This hypothesis is particularly motivated by Bloom (2009), who shows that macroeconomic uncertainty shocks lead to a rapid drop in output, employment and productivity growth.

My research approach comes in three parts. First, I use the cross-sectional asset-pricing test introduced by Fama and MacBeth (1973), with expected real GDP growth and dispersion of beliefs as state variables and German stocks as test assets, to investigate whether expected business conditions and macroeconomic uncertainty can help to explain the cross-sectional variation in German stock returns. Next, I will construct the macroeconomic risk premiums underlying these factors using a portfolio sorting approach to circumvent the errors-in-variables problem inherent in the Fama-MacBeth (1973) methodology. Using rolling window regressions, I form quarterly updated decile portfolios for each factor separately by sorting individual stocks on their return sensitivity to the expected real GDP growth rate and dispersion of beliefs factor, respectively. Each quarter, the risk premium is computed as the spread between the return earned by the portfolios with the highest factor loadings and those with the lowest factor loadings. However, expected GDP growth and macroeconomic uncertainty are not traded assets and are only observable at low frequency, while stock returns can be measured at higher frequency. Therefore, I follow most of the existing literature and construct factor mimicking portfolios that aim to represent the background factors, to increase the number of time-series observations and potentially improve the predictive power of my model.

Regarding the limitations of my work, it is important to mention that the participants of the SPF are asked to provide annual growth expectations for the quarter that is set one year ahead of the latest available data release for the respective variable. The survey, however, is conducted two quarters after the latest official data on those variables is published. Consequently, it cannot be assured that the participants use no additional information at the time the survey takes place to make their forecasts, which potentially limits the predictive power of my model. Another concern remains regarding the ability of dispersion of beliefs to serve as a proxy for economic uncertainty. Several researchers provide contrasting empirical evidence on this issue (see for example Gordani and Söderlind 2003 and Abel et al. 2016). Moreover, as Garcia (2003) points out, changes in expectations might be driven by changes in the set of participants rather than by changed assessments. Another issue worth mentioning is that the t-ratio suggested by Fama and MacBeth (1973) assumes that the asset returns are independently and identically distributed. Ferson and Harvey (1991), however, argue that those t-ratios have to be interpreted with caution, especially in small samples, given the possibility of correlated measurement errors. I will go into more detail on the implications of those issues in section two and three.

The remainder of this study is structured as follows: Section 2 gives an overview of the existing literature related to my research area. In section 3, I discuss the econometric methodology as well as the data set used, whereas in section 4, I present and discuss the results of my various asset-pricing tests. The last section summarizes and concludes.

2 Literature Review

My study fits in the area of research that investigates the effects of expected business conditions and macroeconomic uncertainty on the cross-section of expected stock returns. With regard to the impact of expected business conditions, my work is particularly related to studies that use direct measures of macroeconomic expectations.

Motivated by their finding that standard financial predictors are bad proxies of expected business conditions, Campbell and Diebold (2009) examine the effects of expected business conditions on expected excess stock returns directly, without using any proxies. They use six-month real GDP growth forecasts as a direct measure of expected future business conditions, which they construct from the level forecasts of nominal GDP and consumer price index (CPI) reported in the Livingston survey.[1] However, as the Livingston survey does not provide forecasts on those variables for the current period, they cannot construct one-step-ahead forecasts as usually done in the common literature. Using survey data from 1952 Q1 until 2003 Q2 and lagged two-step-ahead forecasts, they regress excess stock returns on the semiannually growth forecasts constructed from the Livingston survey while controlling for standard financial and macroeconomic predictors. The results show a significant negative correlation between expected excess returns and expected business conditions. They confirm the robustness of their findings, using growth expectations from the U.S. version of the Survey of Professional Forecasters[2] as another direct measure of expected future business conditions. However, they do not further investigate whether their growth expectations measure can help to explain the cross-sectional variation of expected stock returns.

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[1] The Livingston Survey was started in 1946, is conducted twice a year and consists of economists' forecasts of different macroeconomic variables for the U.S. economy, describing for example national output, prices and unemployment. https://www.philadelphiafed.org/research-and-data/real-time-center/livingston-survey

[2] The Survey of Professional Forecasters is provided by the Federal Reserve Bank of Philadelphia and started in 1968 Q4. It is a quarterly survey of currently 32 macroeconomic variables regarding the U.S. economy. https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/

Building on the finding of Campbell and Diebold (2009) that expected stock returns rise when future growth is expected to be low, Goetzmann et al. (2012) use expected real GDP growth rates constructed from the Livingston survey as a state variable in cross-sectional asset-pricing tests. In particular they want to examine whether stocks whose returns comove with business cycles (procyclical stocks) earn higher returns than countercyclical stocks. To test this hypothesis, they first use the cross-sectional asset-pricing test introduced by Fama and MacBeth (1973) with expected real GDP growth as state variable. In particular, their two-factor benchmark model consists of the market excess return and the second semiannual lag of the expected real GDP growth rate. Using 25 size and book-to-market sorted portfolios as test assets, they find that the two-factor model explains a significant portion of cross-sectional variation in asset returns. The premium for expected real GDP growth is significantly positive, which implies that stocks whose returns comove with business cycles indeed earn higher returns. Moreover, they sort individual stocks based on their return sensitivity to the expected real GDP growth rate into decile portfolios, using rolling window regressions. The procyclicality premium is computed as the average monthly return spread between the highest and lowest expected real GDP growth beta portfolios and amounts to 0.43 percent. However, they just include the point forecasts of real GDP growth in their model and ignore the possibility that the cross-sectional dispersion of those point forecasts might absorb some of the explanatory power of expected real GDP growth rates in the cross-section of asset returns. In particular their reported regression coefficients on expected real GDP growth might be systematically over- or underestimated, due to an omitted variable bias. Furthermore, they lack to make use of factor mimicking portfolios in order to increase the number of time-series observations.

Different from Campbell and Diebold (2009) and Goetzmann et al. (2012), who rely on an observable measure of investors expectations, Vassalou (2003) aims to investigate whether a factor mimicking portfolio, capturing news related to future GDP growth, has explanatory power in the cross-section of stock returns. She finds that the constructed GDP growth factor together with the overall market factor can help to explain the cross-sectional variation in expected stock returns. Additionally, she shows that the Fama and French factors (1992, 1993) loose much of their explanatory power once the constructed GDP growth factor is added to the model, suggesting that the factors related to firm size and book-to-market equity mainly contain news regarding future GDP growth.

Regarding my second factor, it is important to keep in mind that macroeconomic uncertainty is latent and must hence be approximated by observable variables. A frequently used proxy for this purpose is based on the dispersion of beliefs among forecasters. The intuition here is that forecasters tend to disagree more when business conditions are volatile (see for example Baetje and Friedrici 2016). However, the common literature provides contrasting evidence on whether or not this is a valid proxy for macroeconomic uncertainty. Using inflation data from the Livingston survey, Bomberger and Frazer (1981) find a substantial positive link between the standard deviation of point forecasts and past forecast errors, letting them suggest that the cross-sectional forecast dispersion serves as a proxy of inflation uncertainty. Zarnowitz and Lambros (1987), on the other hand, note that the inference drawn by Bomberger and Frazer (1981) is inconclusive. They argue that past forecast errors are just one determinant of uncertainty, and that large parts of the relation between the standard deviation of point forecasts and past forecast errors might be driven by the serial correlation of errors from the Livingston survey. Using the predictive probability distributions of individual forecasters as "true" uncertainty, they find that the cross-sectional standard deviations of point forecasts tend to underestimate uncertainty. Lahiri and Sheng (2010) agree that disagreement alone understates the measure of "true" uncertainty. They argue that aggregate forecast uncertainty consists of two parts, the disagreement among point forecasts and the perceived variability of future aggregate shocks. Hence, they conclude that the ability of disagreement alone to serve as a proxy for uncertainty is mainly driven by the stability of the forecasting environment. In particular, they suggest that in periods with large volatility of aggregate shocks, disagreement is not a valid proxy for uncertainty.

Bomberger (1996) again tests the link between disagreement among forecasters and uncertainty empirically, using inflation expectations from the Livingston survey. Treating the conditional variance of individual inflation forecasts as "true" uncertainty and the cross-sectional variance of these point forecasts as disagreement factor, he finds a significant relationship between disagreement among forecasters and uncertainty. Comparing different measures of uncertainty based on inflation and real GDP growth data, provided by the U.S. Survey of Professional Forecasters, Giordani and Söderlind (2003) confirm the ability of disagreement about the point forecast to approximate uncertainty. Lahiri and Sheng (2010), however, disagree with the inference drawn by Bomberger (1996, p. 385) that "if disagreement is to be a good proxy for individual uncertainty, it must also track consensus uncertainty ".

Abel et al. (2016) find no significant link between disagreement and uncertainty, when applying the "true" uncertainty measure of Zarnowitz and Lambros (1987) to point forecasts from the ECB Survey of Professional Forecasters. Bowles et al. (2010) also bring up the limited usefulness of the cross-sectional dispersion of point forecasts in the ECB Survey of Professional Forecasters as proxy of macroeconomic uncertainty. However, they point out that uncertainty measures based on probability distributions come with substantial drawbacks as well. In the ECB Survey of Professional Forecasters, respondents are asked to attach probabilities to specific ranges, yet how the probability is distributed within that range remains unknown, which makes the calculations of standard deviations problematic in practice, especially since the SPF probability distributions frequently deviate from normality (Bowles et al. 2010).

Most of the before mentioned studies have in common that they need to assume some "true" uncertainty when evaluating uncertainty proxies and lack to provide alternative test approaches. Kjellberg and Post (2007), on the other hand, seek to test uncertainty proxies without relying on such explicit assumptions. They evaluate a set of different uncertainty proxies based on the intuition that a reliable proxy should react to unforeseen and exogenous events such as terrorist attacks or outbreaks of war. They find that disagreement and stock market volatility proxies seem to be appropriate measures of uncertainty. However, the predictive probability distribution, used by Zarnowitz and Lambros (1987) as "true" uncertainty, shows no systematic response to the exogenous events, suggesting that this is no appropriate proxy of uncertainty. Another approach, introduced by Baetje and Friedrici (2016), suggests measuring macroeconomic uncertainty as the data revision structure of inflation and real GDP growth rates. Their intuition is that high data uncertainty deteriorates the accuracy of initial data releases, implying that the succeeding data revisions will be large. Using data from the U.S. Survey of Professional Forecasters, they find that the cross-sectional dispersion of beliefs is significantly related to their uncertainty measure.

In absence of a consensus on more appropriate proxies for uncertainty, the disagreement among forecasters remains a likely candidate for the cross-sectional asset-pricing tests within the scope of my research essay.

Regarding the impact of uncertainty on expected stock returns, Veronesi (1999) shows that uncertainty increases market volatility, which in turn leads risk-averse investors to demand higher expected returns as compensation for bearing additional risk when uncertainty is high.

However, he lacks to investigate the cross-sectional pricing ability of investors uncertainty. Ozoguz (2009), on the other hand, builds on the work of Veronesi (1999) and empirically shows that uncertainty proxies constructed from regime-switching models of market return and output can help to explain the cross-sectional variation of stock returns. Ang et al. (2006) investigate how changes in aggregate market volatility are priced in the cross-section of stock returns. They find that stocks with higher exposure to changes in aggregate market volatility earn lower average returns. They motivate this negative cross-sectional risk premium with the intuition stated by Bakshi and Kapadia (2003), that stocks with higher exposure to market volatility risk serve as hedges against economic downturns. The prices of those assets intuitively rise as the demand increases, which in turn lowers their average returns.

Anderson et al. (2009), on the other hand, measure macroeconomic uncertainty as the dispersion of point forecasts regarding output, output deflator and corporate profits provided by the U.S. Survey of Professional Forecasters. Applying the Generalized Method of Moments (GMM) estimation, they find that uncertainty is significantly positive priced. In addition, they sort stocks according to their sensitivities to uncertainty into three distinct portfolios, which are updated each quarter using rolling window regressions. They find that the highest uncertainty beta portfolio on average earns quarterly returns two percent in excess of the lowest uncertainty portfolio, suggesting that stocks whose returns are correlated with uncertainty carry a premium relative to stocks whose returns are uncorrelated with uncertainty. Bali and Zhou (2014) also find a significantly positive market price of uncertainty. They measure uncertainty as the variance risk premium of the aggregate stock market portfolio and provide empirical evidence that their measure of uncertainty is indeed closely linked to economic and financial market uncertainty. The annual return spread between the highest and lowest uncertainty beta portfolios is approximately eight percent, indicating a positive, statistically significant uncertainty premium. Using the cross-sectional regression approach of Fama and MacBeth (1973), they find positive and statistically significant average slope coefficients in the second-pass regression, which again implies a positive statistically significant uncertainty premium. The economic intuition they provide is based on Merton (1973), who suggests that risk-averse investors prefer to hedge against a future cut in consumption opportunities. Bali and Zhou (2014) argue that in times of high aggregate macroeconomic uncertainty, agents tend to reduce their consumption and shift their investments from more to less risky assets, which results in increased expected returns for portfolios that tend to covary more with uncertainty. Bali et al. (2014), on the contrary, find a statistically significant negative uncertainty premium in the cross-section of individual stock returns and provide an economic explanation that also follows the intertemporal hedging demand argument of Merton (1973); the suggested inference, however, is different from the inference drawn by Bali and Zhou (2014). Similar to Bali and Zhou (2014), they argue that agents tend to reduce consumption and investments in times of macroeconomic uncertainty and prefer to hold stocks that are correlated more with macroeconomic uncertainty, since these stocks provide larger returns when uncertainty is high. However, they argue that these stocks work as a hedge against uncertain future downturns in the economy and reduce the risk for individual investors, who in turn accept lower average expected returns from these stocks. They measure uncertainty as the cross-sectional dispersion of GDP point forecasts from the U.S. Survey of Professional Forecasters over the sample period 1968 Q4 to 2012 Q4, finding that the lowest uncertainty beta portfolio earns 6.8 to 8.3 percent more annual return than the highest uncertainty beta portfolio, which is in sharp contrast to Bali and Zhou (2014). Another notable finding of their study is that the negative uncertainty premium is distinguishable from the negative volatility premium found by Ang et al. (2006). Moreover, they construct a broad macroeconomic uncertainty index as the first principal component of seven macroeconomic uncertainty variables from the U.S. Survey of Professional Forecasters and find a statistically significant negative relation between uncertainty index sensitivities and stock returns.

Bali et al. (2014) define the cross-sectional dispersion as the percentage spread between the 75^{th}-percentile and the 25^{th}-percentile of the different point forecasts. Lee and Kim (2014), however, measure the dispersion of beliefs as the standard deviation of real GDP growth forecasts among forecasters from the U.S. Survey of Professional Forecasters and make similar findings. Using the Fama-MacBeth (1973) cross-sectional regression approach, they find that dispersion of beliefs carries a negative risk premium in the stock market. Similar to Bali et al. (2014), they perform a portfolio sorting approach and find that stocks in the lowest dispersion of beliefs beta portfolios earn annually returns that are approximately five percent in excess of those earned by stocks in the highest dispersion of beliefs beta portfolios. Additionally, they test the pricing ability of those return spreads using Fama-MacBeth (1973) cross-sectional regressions and find that the return spreads have a statistically significant pricing ability only when modeled together with the Fama and French (1992, 1993) factors.

3 Methodology

This chapter describes the overall research approach, the underlying data set, as well as the methodology, used to analyze the data with regard to my research purposes. Moreover, I will talk about the validity and reliability of my research approach and present potential drawbacks and limitations.

3.1 Research Approach

As stated before, it might be desirable to use direct measures of macroeconomic expectations, such as expected real GDP growth rates, in cross-sectional asset-pricing tests, rather than noisy financial proxies. However, expected real GDP growth rates are presumably highly correlated with macroeconomic uncertainty, suggesting that ignoring macroeconomic uncertainty will induce an omitted variable bias in the regression coefficient on expected real GDP growth. Hence, the purpose of my study is to investigate whether a model that simultaneously contains the mean and the standard deviation of real GDP growth forecasts from the SPF can help to explain the cross-sectional variation in expected returns in the German stock market. The expected real GDP growth from the SPF can be interpreted as a proxy for expected business conditions, whereas the cross-sectional dispersion of these expectations may serve as a proxy for macroeconomic uncertainty. In particular, my 3-factor model consists of the excess market return, the cross-sectional mean of expected real GDP growth rates, as well as the cross-sectional standard deviation of expected real GDP growth rates. However, expected real GDP growth rates from the SPF are just available at quarterly frequency and for a relatively small time horizon, which limits the number of time series observations in my model. Portfolio returns, on the other hand, are available at high frequency. To potentially increase the predictive power of my model, I construct factor mimicking portfolios that aim to capture expected real GDP growth and macroeconomic uncertainty. I follow most of the existing literature and test my research question using both, cross-sectional regressions and portfolio sorts.

3.2 Data Collection Method

3.2.1 3-Factor Benchmark Model

I use one-year-ahead real GDP growth forecasts from the Survey of Professional Forecasters to construct the proposed measures of growth expectations and macroeconomic uncertainty. The SPF was started in 1999 by the European Central Bank and is a quarterly survey of expectations for the rates of inflation, real GDP growth and unemployment in the euro-zone for several horizons. All participants of the SPF are considered to be experts affiliate with financial or non-financial institutions within the European Union (ECB 2016).[3]

In the context of the SPF, real GDP growth is defined as year-on-year percentage change of real GDP, based on the standardized ESA (European System of National and Regional Accounts) definition (ECB 2016). The participants are asked to provide both, fixed horizon (i.e., rolling) and fixed event (i.e., calendar year) forecasts for short-, medium- and long-term horizons (Bowles et al. 2010). However, I focus on the rolling horizon forecasts for two main reasons, which are already stated by Bowles et al. (2010). The first reason they indicate is the small number of outcomes available for the fixed-event horizon. Secondly, they point out that the information available for the current calendar year forecast significantly differs between the Q1 survey-round and for example the Q4 survey-round.

However, it should be mentioned that the rolling horizon is set one year ahead of the latest official data release of the variable in question and not one year ahead of the date the survey is conducted (Bowles et al. 2010). That is, in the 2013 Q1 survey-round, the latest available official annual GDP growth data was released in 2012 Q3; hence, the one-year-ahead horizon for annual GDP growth forecasts was 2013 Q3.[4] Nevertheless, as the length of the horizon is fixed over time, the data can be considered as quarterly observations on a homogeneous series (Abel et al. 2016).

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[3] A list of institutions who contribute to the SPF can be found on the webpage dedicated to the SPF: http://www.ecb.europa.eu/stats/prices/indic/forecast/html/index.en.html

[4] For further clarification a copy of the 2013 Q1 survey is available on the webpage dedicated to the SPF: http://www.ecb.europa.eu/stats/pdf/spfquestionnaire.pdf?2f26878249f55146410d4b13c741b824

The ECB provides a full dataset of each participants' SPF forecasts, which makes it possible to construct the proposed macroeconomic measures directly from this dataset instead of relying on the rounded figures published on the ECB website. I define the expected real GDP growth measure as the cross-sectional average of individual point forecasts from the SPF:

$$EGDP_t = \frac{1}{N}\sum_{i=1}^{N} EGDP_{i,t} \tag{1}$$

Where:

$EGDP_t$	is the average expected annual real GDP growth rate for the target quarter t
$EGDP_{i,t}$	is the expected annual real GDP growth rate of participant i for the target quarter t
N	is the number of participants in quarter $t-2$, in which the survey for target quarter t is conducted

The macroeconomic uncertainty measure in target quarter t ($STDV_t$) is then calculated as the cross-sectional standard deviation of individual real GDP growth point forecasts:

$$STDV_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(EGDP_{i,t} - EGDP_t)^2} \tag{2}$$

The SPF was first conducted in 1999 Q1 and the latest available survey round was in 2016 Q1. Therefore, the dataset contains forecasts for the target quarters 1999 Q3 ($t = 1$) through 2016 Q3 ($t = 69$).

I aim to investigate the explanatory power of those macroeconomic factors in the cross-section of German stock returns. Therefore, I select stocks of the 100 largest German companies (size is measure by market capitalization) listed on the Frankfurt stock exchange as test assets. Moreover, to match the horizon of the SPF and to be able to calculate annual returns starting in 1999 Q3, the stocks have to be constantly listed since 1998 Q3. As it is not yet possible to calculate annual returns for 2016 Q2 and 2016 Q3, the sample is decreased from 69 quarters to 67 quarters. In particular, I obtain quarterly stock prices from Thomson Reuters Datastream and calculate annual log-returns for the quarters 1999 Q3 ($t = 1$) until 2016 Q1 ($t = 67$):

$$R_{i,t} = \ln P_{i,t} - \ln P_{i,t-4} \tag{3}$$

Where:

$R_{i,t}$ is the annual log-return on stock i in quarter t

$P_{i,t}$ is the official closing price of stock i in quarter t

Excess returns are then calculated, using the 3-month Euro interbank offered rate (EURIBOR) as risk-free rate. EURIBOR 3-month annual rates are obtained from Thomson Reuters Datastream and the excess returns are calculated as:

$$Z_{i,t} = R_{i,t} - Rf_t \tag{4}$$

Where:

$Z_{i,t}$ is the annual excess return on stock i in quarter t

Rf_t is the EURIBOR 3-month annual rate in quarter t

I use the STOXX Europe 600 index as proxy for the market factor. Quarterly index prices are again obtained from Thomson Reuters Datastream and then transformed to annual excess returns using the methodology of equation (3) and (4). Finally, MKT_t is defined as the annual excess return on the market index in quarter t.

3.2.2 Factor Mimicking Portfolios

In subsection 3.6, the 3-factor model is estimated on daily frequency. Instead of the original factor realizations of $EGDP$ and $STDV$, factor mimicking portfolios are used. In order to construct daily excess returns on the factor mimicking portfolios, I calculate daily stock excess returns in addition to the annual excess returns from the previous subsection. I obtain daily stock prices from Thomson Reuters Datastream and calculate daily log-returns for the time horizon 01.04.2009 ($t = 1$) until 20.12.2015 ($t = 1711$):

$$R_{i,t}^d = \ln P_{i,t}^d - \ln P_{i,t-1}^d, \tag{5}$$

where the superscript d indicates a daily time-series to distinguish the variables from their quarterly counterparts obtained in the previous subsection.

Excess returns are again calculated, using the 3-month EURIBOR as risk-free rate. EURIBOR 3-month annual rates are obtained from Thomson Reuters Datastream and transformed to daily rates. The excess returns are then calculated as:

$$Z_{i,t}^{d} = R_{i,t}^{d} - Rf_{t}^{d} \tag{6}$$

Finally, MKT_t^d is defined as the daily excess return on the market index at time t.

3.3 Predictive Return Regression

As a preliminary investigation, I test the ability of my factors to predict future excess market returns, which, as pointed out by Goetzmann et al. (2012), among others, is the qualification for a state variable in cross-sectional asset-pricing tests. In particular, the predictive regression equation is given as follows:

$$MKT_t = \alpha + \beta_1 F_{1,t} + \beta_2 F_{2,t} + \varepsilon_t \tag{7}$$

If the coefficient estimates obtained from equation (7) are statistically significant, this indicates that the factors F_1 and F_2 can predict future excess market returns, and hence serve as state variables in cross-sectional asset-pricing tests.

3.4 Fama-MacBeth Regression

First, I examine the explanatory power of my factors using a version of the cross-sectional asset-pricing test introduced by Fama and MacBeth (1973). This approach involves a two-stage regression. In the first stage, factor loadings are estimated by running a set of single time-series regressions of each test asset's excess returns ($Z_{i,t}$) on the K factors $F_{1,t}$, $F_{2,t}$, … , $F_{K,t}$. In particular, for each asset $i = 1, \dots, N$ the following time-series regression has to be estimated using ordinary least squares (OLS):

$$Z_{i,t} = \alpha_i + \beta_{i,F_1} F_{1,t} + \beta_{i,F_2} F_{2,t} + \cdots + \beta_{i,F_K} F_{K,t} + \varepsilon_{i,t}\,, \quad t = 1, \dots, T \tag{8}$$

Where β_{i,F_1}, β_{i,F_2}, … , β_{i,F_K} are the regression coefficients on the K factors respectively, α_i is the intercept term, $\varepsilon_{i,t}$ is the error term, N is the number of stocks, T is the number of time-series observations and K is the number of factors.

When estimating regression equation (8), I obtain estimates of β_{i,F_1}, β_{i,F_2},…, β_{i,F_K} for each stock i, which I define as $\hat{\beta}_{i,F_1}$, $\hat{\beta}_{i,F_2}$,…, $\hat{\beta}_{i,F_K}$. In the second stage, cross-sectional regressions of excess test asset returns are run on the factor loadings obtained in the first stage, to determine each factor's premium. Using $\hat{\beta}_{i,F_1}$, $\hat{\beta}_{i,F_2}$,…, $\hat{\beta}_{i,F_K}$, obtained from equation (8), I estimate the following cross-sectional regression for every period $t = 1, \dots, T$:

$$Z_{i,t} = \gamma_{0,t} + \gamma_{1,t}\hat{\beta}_{i,F_1} + \gamma_{2,t}\hat{\beta}_{i,F_2} + \cdots + \gamma_{\mathrm{K},t}\hat{\beta}_{i,F_K} + \varepsilon_{i,t}\ ,\ i = 1, \dots, N \tag{9}$$

Where $\gamma_{1,t}$, $\gamma_{2,t}$, …, $\gamma_{\mathrm{K},t}$ are the regression coefficients on the K factors at time t, respectively and $\gamma_{0,t}$ is the intercept term.

Estimating regression (9) by OLS for each period t results in T estimates of $\gamma_{1,t}$, $\gamma_{2,t}$, …, $\gamma_{\mathrm{K},t}$, which we define as $\hat{\gamma}_{1,t}$, $\hat{\gamma}_{2,t}$, …, $\hat{\gamma}_{\mathrm{K},t}$. The average risk premium ($\overline{\hat{\gamma}_k}$) for each factor $k = 1, \dots, K$ is then calculated as the time series average of $\hat{\gamma}_{k,t}$, respectively:

$$\overline{\hat{\gamma}_k} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_{k,t} \tag{10}$$

Following Fama and MacBeth (1973) the t-statistic for the test that $\hat{\gamma}_k$ is different from zero is calculated as:

$$t(\overline{\hat{\gamma}_k}) = \frac{\overline{\hat{\gamma}_k}}{\hat{\sigma}_{\gamma_k}/\sqrt{T}} \tag{11}$$

Where:

$$\hat{\sigma}_{\gamma_k} = \sqrt{\frac{1}{(T-1)}\sum_{t=1}^{T}(\hat{\gamma}_{k,t} - \overline{\hat{\gamma}_k})^2} \tag{11.1}$$

The distribution of $t(\overline{\hat{\gamma}_k})$ is assumed to be Student-t with $(T-1)$-degrees of freedom (see for example Campbell et al. 1997). Moreover, the t-statistic in equation (11), suggested by Fama and MacBeth (1973), assumes that the error terms in equation (9) are independent and identically distributed. This assumption, however, might be violated by the errors-in-variables problem inherent in the two-pass estimation methodology. The true factor loadings are not observable and hence have to be estimated in the first-pass regression. Consequently, the explanatory variables in the second-pass regression are measured with error (Kim 1995). Ferson and Harvey (1991) argue that, given the possibility of correlations in the measurement errors, the t-ratios suggested by Fama and MacBeth (1973) have to be interpreted with caution. In particular, as pointed out by Shanken (1992), the standard errors are underestimated, which leads to an overestimation of the t-statistic in equation (11).

Fama and MacBeth (1973) suggest using portfolios instead of individual assets as dependent variables. They claim that the resulting diversification effect will improve the precision of the beta estimates and hence mitigate the errors-in-variables problem. Lo and MacKinlay (1990), however, argue that while this approach potentially decreases the errors-in-variables problem, sorting portfolios based on common asset characteristics might substantially bias the results of the model. Another approach is introduced by Shanken (1992), who suggests to directly adjust the standard errors in the second-pass regression for the errors-in-variables bias. Campbell et al. (1997) argue that this method, while indeed eliminating the errors-in-variables bias in the t-statistic, does not provide a solution to the possibility that other variables might enter spuriously in the cross-sectional regression equation (9).

As both correction-approaches mentioned above come with drawbacks of their own, I apply an alternative methodology to test the explanatory power of expected GDP growth and macroeconomic uncertainty in the cross-section of expected stock returns. The portfolio sorting approach presented in the next subsection does not rely on cross-sectional regressions and hence circumvents the errors-in-variables problem. However, the t-statistic resulting from equation (9) should be interpreted with caution.

I will first apply the Fama-MacBeth methodology, explained above, to MKT, $EGDP$ and $STDV$, which I call the *"3-factor benchmark model"*. The first-stage regression equation is given below:

Model 1: 3-Factor Benchmark Model:

$$Z_{i,t} = \alpha_i + \beta_{i,mkt} MKT_t + \beta_{i,EGDP} EGDP_t + \beta_{i,STDV} STDV_t + \varepsilon_{i,t}\,, \quad t = 1, \dots, T$$

3.5 Portfolio Sorting

The portfolio sorting approach does not require cross-sectional regressions to test a factors' ability to explain the cross-sectional variation of expected stock returns. The risk premium associated with a specific factor is instead calculated as the return spread between high beta portfolios and low beta portfolios. I form quarterly updated decile portfolios for each factor separately (single-sort) by sorting individual stocks on their return sensitivity to the expected real GDP growth rate and dispersion of beliefs factor, respectively.

Following most of the existing literature, I estimate time-varying factor loadings using 40-quarter rolling window regressions. At the beginning of each quarter $t = 41, \ldots, 67$, individual stock returns are regressed on MKT, $EGDP$ and $STDV$, using past ten years (40 observations) of quarterly observations. The regression model used for estimating the factor loadings is given below:

$$Z_{i,\tau} = \alpha_i + \beta_{i,mkt} MKT_\tau + \beta_{i,EGDP} EGDP_\tau + \beta_{i,STDV} STDV_\tau + \varepsilon_{i,\tau}\ , \quad \tau = t-40, \ldots, t-1 \quad (12)$$

At the beginning of each quarter, the stocks are sorted on their $STDV$ and $EGDP$ factor loadings, respectively, into decile portfolios ($p = 1, \ldots, 10$), using the "xtile"-command in Stata. The portfolios are then held until the beginning of the subsequent quarter. In particular, I start forming portfolios at the beginning of Q3 2009 ($t = 41$) and measure quarterly excess returns from Q3 2009 through Q1 2016 ($t = 67$). Portfolio excess returns at time t are calculated as the equally weighted average of the individual stock excess returns in each portfolio at time t for the $STDV$ and $EGDP$ factor, respectively:

$$Z_{p,t}^k = \frac{1}{N} \sum_{i=1}^{N} Z_{i,t}^k\ , \quad k = EGDP, STDV \qquad (13)$$

Where:

$Z_{p,t}^k$ is the quarterly excess return on portfolio p sorted on factor k at time t

$Z_{i,t}^k$ is the quarterly excess return on stock i in portfolio p sorted on factor k at time t

N is the number of stocks in the particular portfolio p

Each quarter, the premium (SPR_t^k) is computed as the spread between the return earned by the portfolio with the highest factor loadings (portfolio 10) and the portfolio with the lowest factor loadings (portfolio 1) for the $STDV$ and $EGDP$ factor, respectively:

$$SPR_t^k = Z_{10,t}^k - Z_{1,t}^k\,, \quad k = EGDP, STDV \tag{14}$$

If the time-series average return spread ($\overline{SPR^k}$) is statistically significant, this indicates that there is a premium associated with the specific factor. The time-series average return spread for the $STDV$ and $EGDP$ factor is calculated as:

$$\overline{SPR^k} = \frac{1}{T}\sum_{t=1}^{T} SPR_t^k\ , \quad k = EGDP, STDV \tag{15}$$

According to Fabozzi et al. (2010), the standard statistical procedure to test the significance of the mean return spread is to use a Student t-test. I follow this approach and calculate the t-statistic as follows:

$$t(\overline{SPR^k}) = \frac{\overline{SPR^k}}{s_k/\sqrt{T}}\ , \qquad k = EGDP, STDV \tag{16}$$

Where:

$$s_k = \sqrt{\frac{1}{(T-1)}\sum_{t=1}^{T}(SPR_t^k - \overline{SPR^k})^2} \tag{16.1}$$

The distribution of $t(\overline{SPR^k})$ is assumed to be Student-t with $(T-1)$-degrees of freedom. However, Patton and Timmermann (2008) argue that comparing only the mean return spread between the highest and lowest beta portfolios is not sufficient to test for a monotonic relation between the sorting variable and expected returns, because it ignores the return patterns of the remaining portfolios. Concluding for example a negative relationship between the sorting variable and expected returns, based only on return patterns of the highest and lowest beta portfolios, might oversee the possibility that a medium beta portfolio earns higher returns than the lowest beta portfolio. They point out that only a test that simultaneously considers the return patterns on all portfolios can identify such non-monotonic relations

3.6 Factor Mimicking Portfolios

3.6.1 The Mimicking Portfolio Theorem

The mimicking portfolio theorem states that if the perfect asset-pricing model is known, a mimicking portfolio formed by the regression of the discount factor on the asset returns can represent exactly the same pricing information as the original pricing model (Cochrane 2008).

The following illustration strongly relies on the work of Cochrane (2008). Assume we know the true asset-pricing model, which is specified as:

$$P = E(mR), \tag{17}$$

where P denotes the price, m is the discount factor and R is a vector of returns. We now regress the discount factor on the returns, with no constant:

$$m = b'R + \varepsilon, \tag{18}$$

where b are the regression coefficients.

The residuals are uncorrelated with explanatory variables by construction ($E(R\varepsilon) = 0$), so we can rewrite equation (17) as:

$$P = E[(b'R)R], \tag{19}$$

which shows that the payoff $b'R$ is a discount factor as well.

3.6.2 Construction of Factor Mimicking Portfolios

Expected real GDP growth and the macroeconomic uncertainty factor are not traded assets and only observable at low frequency. I therefore follow most of the existing literature and construct factor mimicking portfolios that aim to represent the background factors. In particular, the purpose is to construct a portfolio with unit exposure to the factor, it aims to represent and expected return equal to the risk premium of the same background factor (Asgharian 2004). One advantage when using mimicking portfolios instead of the original factor realization is that we only use the information inherent in the economic factors which is relevant for asset returns, and hence reduce the noise in the underlying asset pricing model (Asgharian 2004). Another main advantage is that asset returns often can be observed at higher frequency than the original factor realizations. That is, I can use daily portfolio returns instead of quarterly expected real GDP growth expectations in my cross-sectional asset-pricing model, which substantially increases the number of time-series observations.

One common approach to construct such factor mimicking portfolios is to take a long position in the portfolio with the highest factor loadings and a short position in the portfolio with the lowest factor loadings, as already done in equation (14). The so constructed zero-investment portfolio is particularly sensitive to the underlying macroeconomic factor (the sorting variable) (Asgharian 2004). As a preliminary investigation, I use the quarterly return spreads from equation (14) as constructed factors in a model alongside the market factor and estimate Fama-MacBeth (1973) regressions, following the methodology of subsection 3.4. I compare the performance of the constructed factors to a model, which includes the original factor realizations over the same time horizon. In addition, I estimate a model containing all five factors simultaneously. In particular the first pass regression equations of the three models, which I call the "*Factor Mimicking Portfolio – Low Frequency Models",* are given below:

Model 2: Factor Mimicking Portfolio – Low Frequency Models:

- *Model 2.1*

$$Z_{i,t} = \alpha_i + \beta_{i,mkt} MKT_t + \beta_{i,SPR_E} SPR_t^{EGDP} + \beta_{i,SPR_S} SPR_t^{STDV} + \varepsilon_{i,t}\ , \quad t = 41, \dots ,67$$

- *Model 2.2*

$$Z_{i,t} = \alpha_i + \beta_{i,mkt} MKT_t + \beta_{i,EGDP} EGDP_t^s + \beta_{i,STDV} STDV_t^s + \varepsilon_{i,t}\ , \quad t = 41, \dots ,67$$

- *Model 2.3*

$$Z_{i,t} = \alpha_i + \beta_{i,mkt} MKT_t + \beta_{i,EGDP} EGDP_t^s + \beta_{i,STDV} STDV_t^s + \beta_{i,SPR_E} SPR_t^{EGDP}$$
$$+\beta_{i,SPR_S} SPR_t^{STDV} + \varepsilon_{i,t}\ , \quad t = 41, \dots ,67$$

Where the superscript s indicates the shortened time horizon ($t = 41, \dots ,67$) to distinguish the variables from their counterparts in the *3-factor benchmark model*.

Of course, this approach is again subject to the errors-in-variables problem, already discussed in subsection 3.4. Another shortcoming is that I loose a substantial amount of time series observations when including the two additional factors, due to the fact that the return spreads are first calculated in Q3 2009, which might deteriorate the predictive power of my model.

However, the main reason for including factor mimicking portfolios was actually to increase the number of time series observations to potentially improve the explanatory power of my model. Expected GDP growth and macroeconomic uncertainty are not traded assets and are only observable at low frequency, while stock returns can be measured at higher frequency. Therefore, I use the daily data obtained in subsection 3.2.2 to calculate daily return spreads on the portfolios constructed in subsection 3.5. Daily portfolio excess returns at time t are calculated as the equally weighted average of individual stocks' daily excess returns in each portfolio at time t, for the $STDV$ and $EGDP$ factor, respectively:

$$Z_{p,t}^{k,d} = \frac{1}{N}\sum_{i=1}^{N} Z_{i,t}^{k,d} \ , \ \ k = EGDP, STDV \tag{20}$$

where the superscript d indicates a daily time-series to distinguish the variables from their quarterly counterparts in equation (13).

The daily premium ($SPR_t^{k,d}$) is computed as the spread between the excess return earned by the portfolio with the highest factor loadings (portfolio 10) and the portfolio with the lowest factor loadings (portfolio 1) for the $STDV$ and $EGDP$ factor, respectively:

$$SPR_t^{k,d} = Z_{10,t}^{k,d} - Z_{1,t}^{k,d}, \quad k = EGDP, STDV \tag{21}$$

Subsequently, I apply the Fama-MacBeth (1973) methodology to a model including the $EGDP$ and $STDV$ factor mimicking portfolios on daily frequency ($SPR_t^{EGDP,d}$ and $SPR_t^{STDV,d}$) alongside the daily market factor (MKT_t^d), which I call the *"Factor Mimicking Portfolio – High Frequency Model"*. The first pass regression equation is given below:

<u>Model 3: Factor Mimicking Portfolio – High Frequency Model:</u>

$$Z_{i,t}^{d} = \alpha_i + \beta_{i,mkt} MKT_t^d + \beta_{i,SPR_E} SPR_t^{EGDP,d} + \beta_{i,SPR_S} SPR_t^{STDV,d} + \varepsilon_{i,t} \ , \quad t = 1, \dots, 1711$$

4 Analysis and Discussion

In this chapter, I analyze and discuss the results of my various asset-pricing tests. First, I investigate the link between $STDV$ and $EGDP$ and show how both series evolve over time. Next, I check whether my suggested factors can predict future excess market returns in order to qualify as a state variable in cross-sectional asset-pricing tests. I then present and discuss the results obtained from the Fama-MacBeth cross-sectional regression approach as well as the results of the portfolio sorting approach, and compare them. Finally, I analyze the results obtained from the cross-sectional asset-pricing tests on factor mimicking portfolios.

4.1 Expected Real GDP Growth and Uncertainty

4.1.1 Evolvement Over Time

As mentioned before, it is reasonable to expect a negative relationship between macroeconomic uncertainty and expected business conditions. That is, I would expect macroeconomic uncertainty to be low when expected real GDP growth is high, and vice versa.

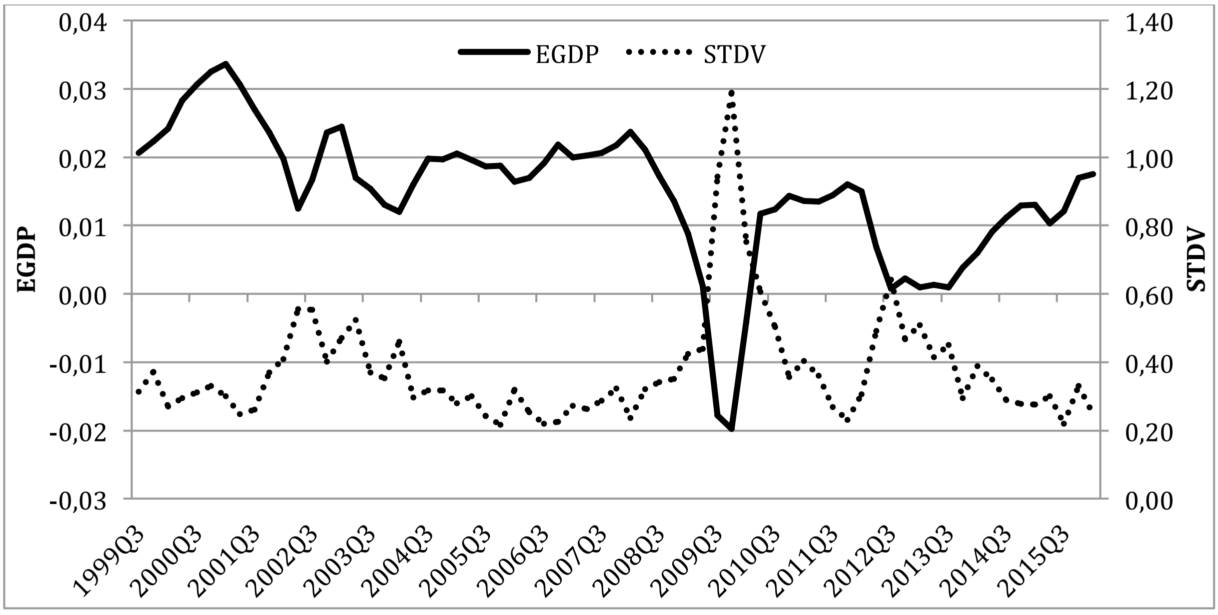

Figure 4.1 Expected real GDP growth and macroeconomic uncertainty

Figure 4.1 shows how the measures of expected annual real GDP growth ($EGDP$) and macroeconomic uncertainty ($STDV$) evolve over the forecast target period 1999 Q3 to 2016 Q1. Following the start of the "dot-com" bubble collapse in March 2000, $EGDP$ first started declining in survey round 2000 Q4, which corresponds to forecast target period 2001 Q2. In particular, $EGDP$ decreased from 3.4 % expected annual growth in target period 2001 Q1 to 1.2 % in 2002 Q2. At the same time, $STDV$ started to increase in survey round 2001 Q1, which corresponds to forecast target period 2001 Q3, and rose from 0.2 in 2001 Q2 to 0.55 in 2002 Q2. The negative impact of the "dot-com" bubble burst was enhanced by the increase in oil prices from 10 USD a barrel in 1999 to 30 USD in the second half of 2000 (EU-Parliament 2001), which further reduced consumption and investments. The uncertainty measure peaked in survey round 2001 Q4 (forecast period 2002 Q2), following the terrorist attacks in the United States on 11 September 2001, while at the same time $EGDP$ reached a new low-point. Thereafter, between forecast period 2002 Q2 and 2008 Q1, uncertainty declined steadily from 0.55 to 0.23, which is way below its mean of 0.38 (see also appendix B, table 1a). Over the same period, $EGDP$ increased from 1.24 % expected annual growth to 2.37 %, which is above its mean of 1.49 %. However, following the start of the global financial crisis in mid 2007, uncertainty started to increase heavily in survey round 2007 Q4 (forecast period 2008 Q2), while expected GDP growth declined substantially. The largest drop in $EGDP$ and the largest jump in $STDV$ can be observed in survey round 2008 Q4, right after the collapse of the investment bank Lehman Brothers on September 15 2008. The uncertainty measure reached its maximum of 1.19 in survey round 2009 Q2, while at the same time $EGDP$ was at its minimum of -1.98 % expected annual growth. Both measures returned back to normal levels during 2010 and early 2011 until the impacts of the euro-zone crisis again substantially increased uncertainty and heavily reduced expected growth, starting in survey round 2011 Q3. After the peak of uncertainty and low-point of expected growth in survey round 2012 Q1, uncertainty steadily declined, while growth expectations improved.

Overall, the patterns of figure 4.1 show strong support for the hypothesis that $EGDP$ and $STDV$ are negatively related. In particular, the correlation between the two series is -0.73 (see appendix B, table 1b). That is, expected GDP growth is indeed low (high) when macroeconomic uncertainty is high (low). Consequently, some of the explanatory power of the expected GDP growth rates in previous studies might be actually due to changes in macroeconomic uncertainty, emphasizing the importance to model both factors simultaneously to circumvent a potential omitted variable bias.

4.1.2 Endogeneity: Omitted Variable Bias

An omitted variable bias occurs, if a relevant explanatory variable, which is correlated with one or more included explanatory variables, has been left out of the regression model. The following example strongly relies on Dougherty (1992, pp. 168-173).

Assume that the true model that determines the dependent variable Y has two explanatory variables (X_1, X_2) and is given by the following population regression function (PRF):

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \ , \tag{22}$$

but due to ignorance or data unavailability, the model is estimated excluding X_2:

$$\hat{Y} = \hat{\alpha} + \hat{\beta}_1 X_1 \tag{23}$$

Consequently, $\hat{\beta}_1$ is calculated as $Cov(X_1, Y)/Var(X_1)$, when in fact the correct expression is:

$$\hat{\beta}_1 = \frac{Cov(X_1,Y)Var(X_2) - Cov(X_2,Y)Cov(X_1,X_2)}{Var(X_1)Var(X_2) - [Cov(X_1,X_2)]^2} \tag{24}$$

By definition, the parameter estimates $\hat{\alpha}$ and $\hat{\beta}_1$ are unbiased if they are on average equal to their true PRF values α and β_1 in equation (22). However, if the true relationship in (22) holds one can show that:

$$E[\hat{\beta}_1] = E\left[\frac{Cov(X_1,Y)}{Var(X_1)}\right] = \beta_1 + \beta_2 \frac{Cov(X_1,X_2)}{Var(X_1)} \ , \tag{25}$$

which indicates that $\hat{\beta}_1$ is biased by an amount equal to $\beta_2 Cov(X_1, X_2)/Var(X_1)$, when X_2 is omitted from the regression equation. In fact, if X_2 is omitted, the estimated coefficient on X_1will include the direct effect of X_1 on Y, as well as a proxy effect when it mimics the effect of X_2 on Y (Dougherty 1992). As $Var(X_1)$ is always positive (unless 0), the direction of the bias depends on the signs of β_2 and $Cov(X_1, X_2)$. Moreover, equation (25) shows that only correlated missing variables cause a bias. If the sample covariance between X_1 and the omitted variable X_2 is exactly zero, the bias term disappears.

The correlation between $EGDP$ and $STDV$ is negative (-0.73), implying that the covariance in the bias term is also negative. Moreover, it is reasonable to expect that the partial effect of $STDV$ on the excess stock returns in the first pass regression will be negative on average, implying a negative β_2. The resulting bias term would be positive; suggesting that $\hat{\beta}_1$ tends to overestimate β_1. However, due to the fact that the true β_2 is an unknown population parameter, we cannot say with certainty whether its sign is positive or negative (Wooldridge 2012).

4.1.3 Multicollinearity

However, including a relevant explanatory variable that is highly correlated with other explanatory variables to circumvent the omitted variable bias might cause another problem, known as multicollinearity. The following explanation is strongly based on Brooks (2014).

Perfect multicollinearity occurs when there is an exact linear relationship between one or more explanatory variables. Assume for example that the relationship between X_1 and X_2 in regression equation (22) is specified by the following linear model:

$$X_2 = \lambda X_1 \tag{26}$$

Given the perfect linear relationship above, it is not possible to estimate all of the coefficients in equation (22), since X_1 and X_2 together only contain enough information to estimate one coefficient. In particular, the $(X'X)$-matrix would not be invertible, since two of the columns would be linear dependent on each other. Consequently, it would not be possible to calculate the OLS-estimates $\hat{\beta} = (X'X)^{-1}X'y$.

In practice, however, it is more likely to find a strong, but not perfect relationship between dependent variables, which is called near multicollinearity. There is no formal test for near multicollinearity, however, as a rule of thumb, near multicollinearity might be present if the correlation between two explanatory variables is above 0.8 or 0.9 in absolute values. This would imply, that multicollinearity might not be a severe problem in my *3-factor benchmark model*, as the correlation between $EGDP$ and $STDV$ is below 0.8. I will test this condition for the remaining models later in this chapter.

4.2 Predictive Return Regression

Table 4.1 shows the regression coefficients, estimated from equation (7), together with the corresponding p-values in parentheses. Expected GDP growth ($EGDP$) and macroeconomic uncertainty ($STDV$), as well as the low frequency factor mimicking portfolios (SPR^{EGDP}, SPR^{STDV}) and high frequency factor mimicking portfolios ($SPR^{EGDP,d}$, $SPR^{STDV,d}$) should predict future excess market returns, in order to qualify as state variables in cross-sectional asset-pricing tests.

Table 4.1 Predictive regression output

	C	$EGDP$	$STDV$	SPR^{EGDP}	SPR^{STDV}	$SPR^{EGDP,d}$	$SPR^{STDV,d}$	R^2
1	0.2611 (0.0639)	-5.5297 (0.1566)	-0.4860 (0.0414)					0.0636
2	0.0771 (0.0080)			0.7012 (0.1550)	-0.7535 (0.0960)			0.1123
3	0.0004 (0.1090)					0.0875 (0.0280)	0.2173 (0.0000)	0.0804

The estimated coefficient on $STDV$ is negative and statistically significant at the 5% level, indicating that $STDV$ has a significant return-predictive ability. In particular, market excess returns are expected to decrease, when macroeconomic uncertainty is high. This is in sharp contrast to Veronesi (1999), Ozoguz (2009) and Anderson et al. (2009), among others, who find that higher uncertainty predicts greater expected market returns. Veronesi (1999), for example, argues that uncertainty increases market volatility, which in turn leads risk-averse investors to demand higher expected returns as compensation for bearing additional risk when uncertainty is high. The estimated coefficient on $EGDP$ is not statistically significant (p-value is 0.1566), indicating that the model does not support the return-predictive ability of $EGDP$. This might deteriorate the validity of the inferences drawn from the cross-sectional regressions in the next sub-section.

Similar findings can be made when using low frequency factor mimicking portfolios instead of the original factor realizations. That is, the estimated coefficient on SPR^{STDV} is again negative and statistically significant at the 10% level, while the coefficient estimate on SPR^{EGDP} is positive and again statistically insignificant.

However, when using factor mimicking portfolios on daily frequency, both coefficient estimates are found to be positive and statistically significant. The positive coefficient estimate on $SPR^{STDV,d}$ is in line with the findings of Veronesi (1999), Ozoguz (2009) and Anderson et al. (2009), while the positive coefficient estimate on $SPR^{EGDP,d}$ stands in contrast to the findings of Campbell and Diebold (2009) and Goetzmann et al. (2012), who find that expected real GDP growth negatively predicts aggregate stock returns. The economic intuition they provide is that agents demand a higher premium when business conditions are expected to be poor, as compensation for the additional risk.

4.3 Fama-MacBeth Regressions

In this subsection, I present and discuss the explanatory power of the *3-factor benchmark model* in the cross-section of German stock returns. Summary statistics for MKT, $EGDP$ and $STDV$ can be found in appendix B table 1a, while table 4.2 below summarizes the results of the Fama-MacBeth cross-sectional regressions. The correlation matrix in appendix B table 1b shows no correlation above 0.8, suggesting that multicollinearity might not be a severe problem in the model.

Table 4.2 Cross-sectional regression output 3-factor benchmark model

	C	MKT	$EGDP$	$STDV$
$\overline{\hat{\gamma}_k}$	0.0495	-0.0262	-0.0023	0.0442
$\hat{\sigma}_{\gamma_k}$	0.1029	0.2255	0.0128	0.2172
$t(\overline{\hat{\gamma}_k})$	3.9415	-0.9502	-1.4835	1.6651
Prob.	0.0002	0.3455	0.1427	0.1006
R^2	0.2578			

Reported are the time-series average slope coefficients ($\overline{\hat{\gamma}_k}$) estimated from the second-pass regression (9), together with their standard deviation ($\hat{\sigma}_{\gamma_k}$), t-statistic ($t(\overline{\hat{\gamma}_k})$) and corresponding two-sided p-value (Prob.). The explanatory variables are the factor loadings obtained from the first pass regression (8), while 'C' denotes the intercept term in the second-pass. 'R^2' is the average R-squared of the second-pass cross-sectional regressions.

The estimated coefficient on the market beta is negative, but not statistically significant (p-value is 0.3455), suggesting that the market beta has no statistically significant explanatory power in the cross-section of stock returns, given the sample at hand. This is in line with previous studies, which found that the market beta, against the implication of the CAPM, has little or no power in explaining the cross-sectional variation of asset returns (Bhandari (1988), Banz (1981), Fama and French (1992 and 1993), among others). The estimated coefficient on the $EGDP$ factor loading is negative but not statistically significant (p-value is 0.1427), implying that expected annual real GDP growth has no statistically significant explanatory power in the cross-section of the test assets' excess returns. This stands in contrast to the inference drawn by Goetzmann et al. (2012), who find a positive and statistically significant factor risk premium, suggesting that expected real GDP growth from the Livingston survey helps to explain the cross-section of expected returns. However, my results might be driven by the small number of time-series observations as well as the weak return-predictive ability of $EGDP$, found in subsection 4.2. The estimated coefficient on the $STDV$ factor loading is positive and close to statistical significance (the two-tailed critical value of a t-distribution with 66 degrees of freedom and 10% significance level is 1.6683). This suggests that the model at least provides some support for the explanatory power of $STDV$ in the cross-section of the test assets' returns, even though the relationship is, strictly speaking, not statistically significant. However, the positive sign of the coefficient implies that stocks whose returns correlate more with the macroeconomic uncertainty measure earn higher returns, which is in line with some previous studies. Anderson et al. (2009) as well as Bali and Zhou (2014) find a positive and statistical significant uncertainty premium in the cross-section of stock returns. Bali and Zhou (2014) argue that in times of high aggregate macroeconomic uncertainty agents tend to reduce their consumption and shift their investments from more to less risky assets, which results in increased expected returns for portfolios that tend to covary more with uncertainty. However, there are also contradicting findings. Bali et al. (2014) and Lee and Kim (2014) find a significantly negative uncertainty premium in the cross-section of individual stock returns. They, on the other hand, argue that stocks whose returns are correlated more with macroeconomic uncertainty work as a hedge against uncertain future downturns in economy and reduce the risk for individual investors, who in turn accept lower average expected returns from these stocks. Summing up, the existing empirical findings on the sign of the uncertainty premium are conflicting and my *3-factor benchmark model* is not able to contribute any statistically significant new evidence; the tendency, however, is towards a positive uncertainty premium.

4.4 Portfolio Sorts

In this subsection, I present the results from the portfolio sorting approach and compare them to the findings obtained from the cross-sectional regressions in the previous section. Table 4.3 reports the characteristics of the decile portfolios sorted on the stocks' return sensitivity to expected real GDP growth.

Table 4.3 Decile portfolios sorted on EGDP

rank	1	2	3	4	5	6	7	8	9	10	10-1
$\overline{\hat{\beta}_{EGDP}}$	-33.92	-14.33	-7.34	-2.79	0.72	4.22	7.73	11.68	17.12	32.09	
$\overline{Z_p^{EGDP}}$(%)	3.96	3.28	2.79	2.75	2.18	2.19	3.40	2.35	2.09	2.51	-1.45
s_p^{EGDP}	0.19	0.13	0.12	0.12	0.13	0.14	0.14	0.15	0.18	0.20	0.09
t-stat.	1.09	1.32	1.20	1.17	0.87	0.83	1.31	0.84	0.59	0.66	-0.87
Prob.	0.28	0.20	0.24	0.25	0.39	0.42	0.20	0.41	0.56	0.51	0.39
N	10	10	10	10	10	10	10	10	10	10	

The portfolio rank '1' indicates the portfolio containing the lowest $EGDP$-beta stocks, whereas rank '10' stands for the portfolio with the highest $EGDP$-beta stocks. '10-1' denotes the portfolio constructed as the return spread between portfolio '10' and portfolio '1'. For each portfolio the average $EGDP$-beta of member stocks ($\overline{\hat{\beta}_{EGDP}}$) is reported, as well as the average quarterly excess return in percentage ($\overline{Z_p^{EGDP}}$), together with its standard deviation (s_p^{EGDP}), t-statistics (t-stat.) and two-sided p-value (Prob.). 'N' is the average number of stocks in the particular portfolio.

Each portfolio contains 10 stocks over the whole holding period of 27 quarters, indicating that each portfolio is well populated. Moreover the first row suggests, that the distribution of average $EGDP$-betas is quite symmetric, with an average $EGDP$-beta of -33.92 in the lowest portfolio and 32.09 in the highest portfolio. Portfolio 1 earns the highest average quarterly excess return (3.96%), while the lowest quarterly excess return is earned by portfolio 9 (2.09%). In particular, $\overline{Z_p^{EGDP}}$ steadily decreases with the portfolio rank from 3.96% in portfolio 1 to 2.19% in portfolio 6, before it jumps back to 3.40% in portfolio 7 (see also appendix C, figure 1). The average excess return spread between portfolio 10 and portfolio 1 is -1.45% per quarter, suggesting that stocks with higher sensitivities to the growth expectations measure earn lower returns. This stands in contrast to the result of Goetzmann et al. (2012), who find an average return spread between the highest and lowest expected real GDP growth beta portfolio of 0.43% per month. However, the average return spread in my model is not statistically significant (p-value is 0.39), making it impossible to draw any reliable inferences.

Table 4.4 reports the characteristics of the decile portfolios sorted on the stocks' return sensitivity to the macroeconomic uncertainty measure.

Table 4.4 Decile portfolios sorted on STDV

rank	1	2	3	4	5	6	7	8	9	10	10-1
$\overline{\hat{\beta}_{STDV}}$	-1.89	-0.78	-0.39	-0.14	0.02	0.17	0.33	0.48	0.72	1.61	
$\overline{Z_p^{STDV}}$(%)	3.46	3.61	2.41	3.34	2.52	2.36	1.73	3.00	1.77	3.31	-0.15
s_p^{STDV}	0.18	0.14	0.14	0.13	0.13	0.14	0.13	0.15	0.17	0.19	0.10
t-stat	1.02	1.32	0.90	1.37	1.01	0.87	0.66	1.07	0.54	0.89	-0.08
Prob.	0.32	0.20	0.38	0.18	0.32	0.39	0.51	0.29	0.59	0.38	0.94
N	10	10	10	10	10	10	10	10	10	10	

Portfolio rank '1' again indicates the portfolio containing the lowest $STDV$-beta stocks, whereas rank '10' stands for the portfolio with the highest $STDV$-beta stocks. '10-1' denotes the portfolio constructed as the return spread between portfolio '10' and portfolio '1'. For each portfolio the average $STDV$-beta of member stocks ($\overline{\hat{\beta}_{STDV}}$) is reported, as well as the average quarterly excess return in percentage ($\overline{Z_p^{STDV}}$), together with its standard deviation (s_p^{STDV}), t-statistics (t-stat.) and two-sided p-value (Prob.). 'N' is the average number of stocks in the particular portfolio.

Each portfolio is well populated and the distribution of $\overline{\hat{\beta}_{STDV}}$ appears to be quite symmetric, with an average $STDV$-beta of -1.89 in the lowest portfolio and 1.61 in the highest portfolio. Portfolio 2 earns the highest average quarterly excess return (3.61%), while the lowest average quarterly excess return is earned by portfolio 7 (1.73%). However, as illustrated in appendix C, figure 1, $\overline{Z_p^{STDV}}$ does not seem to follow any systematic pattern across the decile portfolios; it rather seems to move up and down without following any specific trend. The average quarterly excess return spread between portfolio 10 and portfolio 1 is negative (-0.15%) but insignificant (p-value is 0.94). This suggests that there is no statistically significant premium associated with my macroeconomic uncertainty measure, given the sample at hand. In contrast, Bali and Zhou (2014) find a positive statistically significant return spread between the highest and lowest uncertainty beta portfolio of approximately 8% per annum. Bali et al. (2014) and Lee and Kim (2014), however, find a negative statistically significant annual return spread between the highest and lowest uncertainty beta portfolio of approximately -7% and -5%, respectively.

4.5 Factor Mimicking Portfolios

4.5.1 Low Frequency Data

First, I present and discuss the results obtained from the three "*factor mimicking portfolio – low frequency"* models, specified in section 3.6.2. Summary statistics of the factors for the shortened time horizon 2009 Q3 to 2016 Q1 can be found in appendix B, table 2a, while table 4.5 below summarizes the results of the Fama-MacBeth cross-sectional regressions.

Table 4.5 Factor Mimicking Portfolio – Low Frequency Models

	C	MKT	$EGDP_S$	$STDV_S$	SPR^{EGDP}	SPR^{STDV}	R^2
2.1	0.0441	0.0371			-0.0066	-0.0224	0.3735
	(0.0003)	(0.1982)			(0.7981)	(0.3535)	
2.2	0.0394	0.0371	0.0046	-0.0771			0.3807
	(0.0008)	(0.1984)	(0.0285)	(0.1106)			
2.3	0.0428	0.0359	0.0047	-0.0612	-0.0420	-0.0512	0.4848
	(0.0002)	(0.2143)	(0.0255)	(0.2075)	(0.1722)	(0.0583)	

Reported are the time-series average slope coefficients estimated from the second-pass regression (9), together with their corresponding two-sided p-values in parentheses. The explanatory variables are the factor loadings estimated from the first pass regression (8), while 'C' denotes the intercept term in the second-pass. 'R^2' is the average R-squared of the second-pass cross-sectional regressions.

In accordance with the findings from the *3-factor benchmark model* in subsection 4.3, the estimated coefficient on the market beta is insignificant in all three models, supporting the hypothesis that the market beta has no statistically significant explanatory power in the cross-section of expected stock returns. In contrast to the *3-factor benchmark model*, the estimated coefficient on the $EGDP$ factor loading in *model 2.2* and *model 2.3* is now positive and statistically significant at the 5% level, implying that expected annual real GDP growth has statistically significant explanatory power in the cross-section of the test assets' returns, given the shortened time period. This is in line with Goetzmann et al. (2012), who find a positive and statistically significant factor risk premium. However, as shown in appendix B, table 2b, the correlation between $EGDP_s$ and $STDV_s$ is -0.88, suggesting that the model might be influenced by multicollinearity. Therefore, the results have to be interpreted with caution.

The estimated coefficients on the SPR^{EGDP} and SPR^{STDV} factor loadings are insignificant when modeled solely alongside the market factor (*model 2.1*). The estimated coefficient on the SPR^{EGDP} factor loading remains insignificant when modeled alongside the original factor realizations in addition to the market factor (*model 2.3*), while the coefficient estimate on the SPR^{STDV} factor loading turns statistically significant at the 10% level. Summing up, SPR^{EGDP} does not seem to have any explanatory power at all, when measured at low frequency, while the $STDV$ mimicking factor seems to have more explanatory power in the cross-section of the test assets' excess returns than the original $STDV$ factor realization, only when measured alongside the original factor realization. The negative coefficient estimate on the $STDV$ mimicking factor in *model 2.3*, however, stands in contrast to the positive $STDV$ coefficient found in the *3-factor benchmark model* in subsection 4.3, though the coefficient was strictly speaking not statistically significant. However, it is in line with the intuition that stocks whose returns are correlated more with macroeconomic uncertainty work as a hedge against uncertain future downturns in economy and reduce the risk for individual investors, who in turn accept lower average expected returns from these stocks (Bali et al. 2014, Lee and Kim 2014). But again these results should be interpreted with caution, due to the possible multicollinearity problem that might arise from the high correlation of SPR^{STDV} with $STDV_s$ (0.73) and SPR^{EGDP} (0.78), as shown in appendix B, table 2b.

4.5.2 High Frequency Data

Finally, I present and discuss the results obtained from the "*factor mimicking portfolio – high frequency"* model, specified in section 3.6.2. Summary statistics of the factors at daily frequency can be found in appendix B, table 3a, while table 4.6 below summarizes the results of the Fama-MacBeth cross-sectional regressions.

Table 4.6 Factor Mimicking Portfolio – High Frequency Models

	C	MKT	$SPR^{EGDP,d}$	$SPR^{STDV,d}$	R^2
$\overline{\hat{\gamma}_k}$	0.0002	0.0005	-0.0013	-0.0002	0.1270
$\hat{\sigma}_{\gamma_k}$	0.0046	0.0136	0.0192	0.0155	
$t(\overline{\hat{\gamma}_k})$	1.5512	1.6005	-2.7325	-0.5309	
Prob.	0.1210	0.1097	0.0063	0.5955	

Reported are the time-series average slope coefficients ($\overline{\hat{\gamma}_k}$) estimated from the second-pass regression (9), together with their standard deviation ($\hat{\sigma}_{\gamma_k}$), t-statistic ($t(\overline{\hat{\gamma}_k})$) and corresponding two-sided p-value (Prob.). The explanatory variables are the factor loadings obtained from the first pass regression (8), while 'C' denotes the intercept term in the second-pass. 'R^2' is the average R-squared of the second-pass cross-sectional regressions.

In contrast to *model 2.1* and *model 2.3*, the estimated coefficient on the *EGDP* factor mimicking portfolio is now statistically significant at the 1% level when estimated at daily frequency, while the coefficient estimate on the $STDV$ factor mimicking portfolio turns insignificant. The negative sign of the estimated coefficient on the *EGDP* factor mimicking portfolio, however, stands in contrast to the statistically significant positive coefficient on the original factor realization ($EGDP$) in *model 2.2* and *model 2.3*, suggesting that the factor mimicking portfolio might not be a good proxy of the original factor realization. Again, one has to be aware of a possible multicollinearity problem, caused by the high correlation (0.81) between $SPR^{EGDP,d}$ and $SPR^{STDV,d}$ (see appendix B, table 3b).

4.6 Summary

The portfolio sorting approach in section 4.4 suggests that there is no statistically significant premium associated with either expected real GDP growth or macroeconomic uncertainty. The Fama-MacBeth regression approach, however, leads to some contradicting results, which are summarized in table 4.7 below. Reported are the signs of the second-pass regression coefficients estimated from *model 1* to *model 3*, respectively. *, ** and *** represent significance at 10%, 5%, and 1%, respectively.

Table 4.7 Fama-MacBeth Regressions Summary

Model	MKT	$EGDP$	$STDV$	SPR^{EGDP}	SPR^{STDV}
1	-	-	+		
2.1	+			-	-
2.2	+	+**	-		
2.3	+	+**	-	-	-*
3	+			-***	-

In accordance with the common literature, the estimated coefficient on the market beta is insignificant in all five models, supporting the hypothesis that market beta has no statistically significant explanatory power in the cross-section of expected stock returns. The $EGDP$ factor seems to carry a significant positive risk premium in the cross section of German stocks over the time horizon Q3 2009 to Q1 2016. The negative and statistically insignificant coefficient in *model 1*, however, shows that this relationship does not hold for the whole sample horizon of Q3 1999 to Q1 2016. $STDV$, on the other hand, seems to have no statistically significant power in the cross-section of German stock returns, as the coefficient estimates are insignificant in all three models. However, one should keep in mind that this result might also be due to the possible multicollinearity problem caused by the high correlation between $EGDP$ and $STDV$. The coefficient on the $EGDP$-mimicking portfolio is negative in all models, but only statistically significant when measured at daily frequency. The negative sign, however, stands in contrast to the positive sign indicated for the $EGDP$ factor, suggesting that the mimicking portfolio and the original factor realization contain different information. The coefficient on the $STDV$-mimicking portfolio is negative in all models, but only statistically significant when measured at quarterly frequency alongside the original factor realizations of $EGDP$ and $STDV$.

The overall results provide more evidence for a premium associated with the $EGDP$ factor than for a premium on the $STDV$ factor; however, the results might be influenced by multicollinearity.

5 Conclusion

The present study investigates whether the mean and the standard deviation of real GDP growth forecasts from the ECB Survey of Professional Forecasters can help to explain the cross-sectional variation of expected returns in the German stock market. The expected real GDP growth from the SPF can be interpreted as a proxy for expected business conditions, whereas the cross-sectional dispersion of these expectations may serve as a proxy for macroeconomic uncertainty. The motivation to model both factors simultaneously comes from the potential omitted variable bias, which might occur when both factors are modeled separately. In particular, my *3-factor benchmark model* consists of the market excess return, the cross-sectional mean of expected real GDP growth rates ($EGDP$), as well as the cross-sectional standard deviation of expected real GDP growth rates ($STDV$). However, the expected GDP growth factor and the macroeconomic uncertainty factor are not traded assets and only observable at quarterly frequency. Therefore, I construct factor mimicking portfolios that aim to represent the background factors and can be measured at higher frequency. I follow most of the existing literature and test my research question using both, cross-sectional regressions and portfolio sorts.

Applying the Fama-MacBeth (1973) cross-sectional regression approach, I find that none of the factors in the *3-factor benchmark model* has statistically significant explanatory power in the cross-section of stock returns, given the sample at hand. Using portfolio sorts, I again find that there is no statistically significant premium associated with expected real GDP growth rates and my macroeconomic uncertainty measure, given the sample at hand. I form quarterly updated decile portfolios for each factor separately by sorting individual stocks on their return sensitivity to the expected real GDP growth rate and macroeconomic uncertainty factor, respectively. The risk premium associated with a specific factor is calculated as the return spread between the highest beta portfolio and lowest beta portfolio. The average quarterly excess return spread between the highest and lowest $STDV$-beta portfolio is negative (-0.15%), but insignificant (p-value is 0.94), whereas the average excess return spread between the highest and lowest $EGDP$-beta portfolio is -1.45% per quarter, but also not statistically significant.

Factor mimicking portfolios are constructed starting in Q3 2009 rather than at the beginning of my sample period in Q3 1999, because 40-quarter rolling window regressions are used to form those portfolios. Given this shortened time horizon, the premium associated with the $EGDP$ factor turns positive and statistically significant at the 5% level, both when measured in the 3-factor model or alongside the factor mimicking portfolios. The cross-sectional regression coefficient on the $STDV$ factor, however, remains insignificant. This might also be driven by a potential multicollinearity problem, induced by the high correlation between $EGDP$ and $STDV$ over both horizons. The coefficient on the $EGDP$-mimicking portfolio is negative, both at quarterly and daily frequency, but only statistically significant when measured at daily frequency. However, the negative sign stands in contrast to the positive sign indicated for the original $EGDP$ factor, suggesting that the mimicking portfolio and the original factor realization contain different information. The coefficient on the $STDV$-mimicking portfolio is negative in both models, but in contrast to the $EGDP$-mimicking portfolio only statistically significant when measured at quarterly frequency alongside the original factor realizations of $EGDP$ and $STDV$.

The overall results provide more evidence for a premium associated with expected real GDP growth than for a premium on the macroeconomic uncertainty factor. However, the results are to some extend contradicting and might be influenced by multicollinearity. One possible remedy to overcome multicollinearity problems is to increase the number of time-series observations; consequently, more reliable conclusions might be possible as further survey data becomes available.

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Appendix A: Variable Descriptions

$EGDP_t$	is the average expected annual real GDP growth rate for the target quarter t
$STDV_t$	is the cross-sectional standard deviation of real GDP growth forecasts for the target quarter t
MKT_t	is the annual excess return on the STOXX Europe 600 index in quarter t
MKT_t^d	is the daily excess return on the STOXX Europe 600 index at time t
Rf_t	is the EURIBOR 3-month annual rate in quarter t
Rf_t^d	is the EURIBOR 3-month daily rate at time t
$Z_{i,t}$	is the annual excess return on stock i in quarter t
$Z_{i,t}^d$	is the daily excess return on stock i at time t
$Z_{p,t}^k$	is the quarterly excess return on portfolio p sorted on factor k at time t
$Z_{p,t}^{k,d}$	is the daily excess return on portfolio p sorted on factor k at time t
SPR_t^k	is the spread between the quarterly excess return on the portfolio with the highest and the lowest loadings on factor k, in quarter t
$SPR_t^{k,d}$	is the spread between the daily excess return on the portfolio with the highest and the lowest loadings on factor k, at time t

Appendix B: Summary Statistics

Table 1a: Summary statistics 3-factor benchmark-model

	Mean	Max.	Min.	Std. Dev.	T	Frequ.	Start	End
MKT	-0.0048	0.3688	-0.5583	0.2169	67	quarterly	1999:Q3	2016:Q1
$EGDP$	0.0149	0.0336	-0.0198	0.0100	67	quarterly	1999:Q3	2016:Q1
$STDV$	0.3774	1.1881	0.2169	0.1650	67	quarterly	1999:Q3	2016:Q1

Table 1b: Correlation Matrix 3-factor benchmark-model

	MKT	$EGDP$	$STDV$
MKT	1.00		
$EGDP$	0.02	1.00	
$STDV$	-0.18	-0.73	1.00

Table 2a: Summary statistics Factor Mimicking Portfolio – Low Frequency

	Mean	Max.	Min.	Std. Dev.	T	Frequ.	Start	End
MKT_s	0.0681	0.3688	-0.3350	0.1367	27	quarterly	2009:Q3	2016:Q1
$EGDP_s$	0.0072	0.0175	-0.0198	0.0095	27	quarterly	2009:Q3	2016:Q1
$STDV_s$	0.4396	1.1881	0.2202	0.2252	27	quarterly	2009:Q3	2016:Q1
SPR^{EGDP}	-0.0145	0.1850	-0.1745	0.0872	27	quarterly	2009:Q3	2016:Q1
SPR^{STDV}	-0.0015	0.2908	-0.1184	0.0956	27	quarterly	2009:Q3	2016:Q1

Table 2b: Correlation Matrix Factor Mimicking Portfolio – Low Frequency

	MKT_s	$EGDP_s$	$STDV_s$	SPR^{EGDP}	SPR^{STDV}
MKT_s	1.00				
$EGDP_s$	0.28	1.00			
$STDV_s$	-0.22	-0.88	1.00		
SPR^{EGDP}	0.04	-0.37	0.44	1.00	
SPR^{STDV}	-0.18	-0.63	0.73	0.78	1.00

Table 3a: Summary statistics Factor Mimicking Portfolio – High Frequency

	Mean	Max.	Min.	Std. Dev.	T	Frequ.	Start	End
MKT^d	0.0004	0.0690	-0.0548	0.0111	1711	daily	01.04.09	30.12.15
$SPR^{EGDP,d}$	-0.0002	0.0442	-0.0626	0.0110	1711	daily	01.04.09	30.12.15
$SPR^{STDV,d}$	0.0000	0.0468	-0.0596	0.0107	1711	daily	01.04.09	30.12.15

Table 3b: Correlation Matrix Factor Mimicking Portfolio – High Frequency

	MKT^{d}	$SPR^{EGDP,d}$	$SPR^{STDV,d}$
MKT^{d}	1.00		
$SPR^{EGDP,d}$	0.26	1.00	
$SPR^{STDV,d}$	0.28	0.81	1.00

Table 1a, 2a and 3a show the mean, the maximum (Max.), the minimum (Min.), the standard deviation (Std. Dev.), the number of time-series observations (T), the frequency of time-series observations (Frequ.) and the starting and ending dates for all factors in the three different models, respectively. Table 1b, 2b and 3b report the correlation matrices for these variables.

Appendix C: Analysis

Figure 1: Excess return on decile portfolios

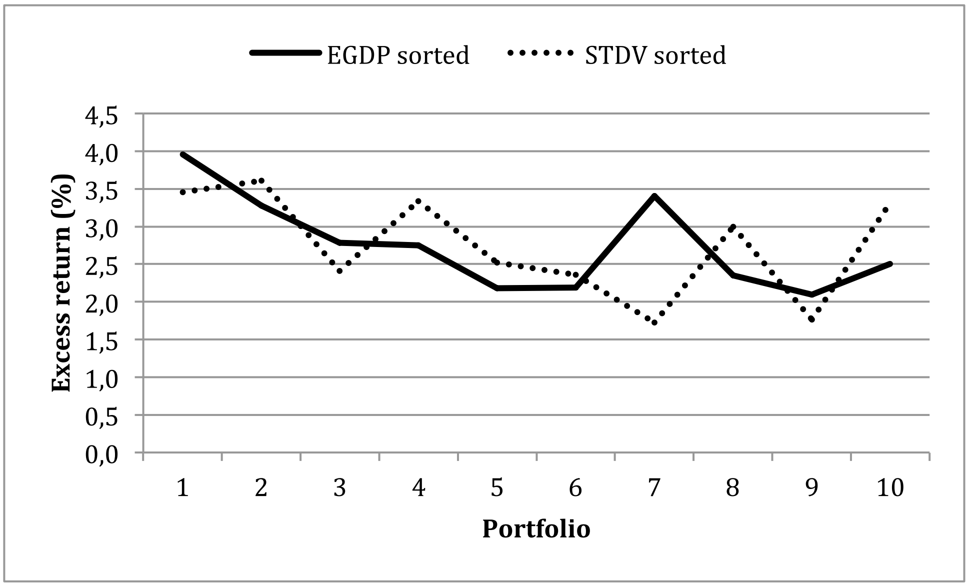

Figure 1 illustrates the average quarterly excess return earned by decile portfolios of stocks sorted on their EGDP-sensitivities ('EGDP sorted') and decile portfolios of stocks sorted on their STDV-sensitivities ('STDV sorted'). Portfolio rank '1' indicates the portfolio containing stocks with the lowest factor sensitivities, whereas rank '10' stands for the portfolio containing stocks with the highest factor sensitivities.