Good and Bad Macroeconomic Uncertainty: Implications for Bond Risk Premia

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ABSTRACT

This paper explores the predictive power of macroeconomic uncertainty on bond risk premia. We decompose quarterly survey data into good and bad uncertainty components by estimating positive and negative semi-variances. Building on theoretical evidence, these uncertainties are assumed to feed into future positive and negative shocks to consumption. In line with our predictions, we find that good (bad) macroeconomic uncertainty predicts a decrease (increase) in future excess returns as well as an increase (decrease) in future economic activity. In addition to this, we document that in the cross section, good (bad) uncertainty contributes positively (negatively) to risk premia, indicating that bonds indeed have high payoffs in bad states of the world and that agents pay a premium for this insurance. Further, we find that our measures of uncertainty add new information not contained in the yield curve and that they are robust once controlled for other sources of macroeconomic uncertainty. Taken together, we present a new characterization and potential explanation of the previously documented countercyclical component in bond risk premia. We also strengthen the view that decomposition of uncertainty provide additional predictive value compared to measures of aggregate uncertainty.

Keywords: Macroeconomic uncertainty, Bond risk premia, Countercyclical, Semi-variance

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I. Introduction

In the aftermath of the Great Recession, Central Banks and policy rates have become the center of attention in both financial news and in economic discussions. We have observed low inflation, low salary growth and low consumer confidence, all of this happening in a low, or even negative, interest rate environment. This is troublesome for economic theory as cheap financing is expected to generate increases in consumption and inflation. Such puzzling phenomenon has sparked a widespread research interest, ourselves included, in how uncertainty influences the decisions taken by firms, consumers and investors. Accordingly, our paper sets out to explore one channel through which uncertainty potentially plays an integral role in financial markets, namely how macroeconomic uncertainty is related to bond risk premia. In particular, we implement our investigation by highlighting the differences between good and bad macroeconomic uncertainty. To give an insightful example of how good and bad uncertainties might transpire in the real economy we refer to Segal, Shaliastovich, and Yaron (2014) and consider the episodes of the mid-1990s and the fall of 2008. The first episode was characterized by a technological revolution caused by the explosion of the Internet and the uncertainty during this period can best be described by the question: *how good of an impact will the Internet have on the real economy?*. The second episode was directly after the collapse of the mortgage market and the bankruptcy of Lehman Brothers, which can be characterized by agents being uncertain about *how bad will this Crash be for the real economy?*. Based on this intuitive example, we argue that the decomposition of uncertainties can help in understanding the behavior of bond risk premia and also, the potential link to the real economy.

Although there is a vast body of research investigating the behavior of risk premia in bond markets, there is to the best of our knowledge, little or potentially no research looking at good and bad macroeconomic uncertainty and their impact on bond risk premia. We ask ourselves if movements in macroeconomic uncertainty bear any direct relation to bond risk premia. More specifically, we ask if it is possible to fine-tune any relationship by decomposing good and bad macroeconomic uncertainty. These are relevant questions as recent literature indicates that macroeconomic risks indeed are important to understand the time variation and behavior of bond risk premia. Using this insight, we try to address the questions outlined above by building our empirical investigation on the model provided by Segal et al. (2014). In this setting, good and bad uncertainties stem from the positive and negative semi-variances of the underlying distribution of macroeconomic variables and these uncertainty measures drive positive and negative shocks to consumption. Accordingly, in the wake of high good (bad) uncertainty in time t, the volatility to the positive (negative) shocks to consumption increase in time $t+1$.

Using survey data of individual forecasts on Real GDP, Inflation and Real Personal Consumption Expenditures for the U.S. economy, we estimate aggregate, good and bad uncertainty measures. We build forward looking good and bad uncertainty proxies from the semi-variances of each forecast distribution within each quarter. We use these proxies for each macroeconomic variable to assess whether decomposing uncertainty provides value in forecasting future excess returns. To do so, we regress future excess bond returns for maturities spanning 2 to 5 years on (i) aggregate uncertainty and on (ii) good and bad uncertainty proxies. From the regressions in (i), we observe low explanatory values and, for most parts, statistically insignificant results on the coefficients. Once decomposing the uncertainty measure into good and bad components as in (ii), we are able to increase the explanatory value by at least 5 percentage points. More importantly, we find that good (bad) uncertainty for all three variables predicts decreased (increased) excess bond returns between t and $t+1$. However, we do not find simultaneous statistical significance for both good and bad uncertainty loadings. One potential issue we face is that the individual proxies for uncertainty carry too much noise. To cope with this, we perform a Principal Component Analysis to construct three uncertainty indices: one good, one bad and one aggregate index. We use the first component, which in our data explains around 70 percent of the total variation for all indices. We re-estimate the predictive regressions to see if we can increase the explanatory power. In the case of aggregate uncertainty index, we find a notably higher explanatory value compared to the individual regression specifications. We also document a positive loading on aggregate uncertainty, which is in line with our expectations, although barely significant. In the second regression, we do find that the coefficients on good (bad) uncertainty are negative (positive), which is in line with our predictions and our previous evidence. More importantly, we increase the explanatory power to 16 percent for the short term bonds and to an R^2 of 12 percent for the equally weighted portfolio across all maturities. We find evidence that both good and bad uncertainty loadings become statistically significant at conventional levels. This suggests that we have created indices which are more informative compared to the individual uncertainty measures, indicating that we indeed are able to fulfill our goal of refining the uncertainty proxies. Thus, we find evidence that decomposing uncertainty provides valuable information about bond risk premia and that bad (good) uncertainty predict increased (decreased) future excess returns.

Our second goal is to provide a link between real economic activity and bond risk premia that goes through our uncertainty measures. To do so, we project future realized growth in industrial production from our uncertainty indices. We document a negative, insignificant, loading on aggregate uncertainty with an R^2 that is close to zero. Once again, when decomposing the uncertainty into good and bad parts, we increase the explanatory value to roughly 7 percent. Further, we find evidence that good (bad) uncertainty predicts an increase (decrease) in economic activity over the following year. Combining our predictive results so far, we argue that good and bad uncertainty can help to explain the commonly documented countercyclical component in bond risk premia.

To shed light on the actual importance and robustness of our findings we perform two regressions in which we control for both financial factors and other sources of macroeconomic uncertainty. Firstly, we regress future excess return onto our uncertainty indices and control for the five forward factors derived by Cochrane and Piazzesi (2005). We find evidence indicating that our good and bad uncertainty measures maintain their statistical significance and that the size of the coefficients are nearly unchanged. We also document an increase in the explanatory value of around 3 to 5 percentage points, suggesting that our uncertainty indices provide new information regarding bond risk premia over and above the information contained in the yield curve. Secondly, we regress future excess returns onto our uncertainty indices while controlling for the broad uncertainty measure constructed by Ludvigson, Ng, and Jurado (2015). The results suggests that our good and bad uncertainty subsumes all significance such factor had on a stand alone basis when predicting future excess returns. Taking these two control regressions together, we are confident that our good and bad uncertainty measures are of importance in understanding the risk premia in bonds. As for robustness, we perform one out-of-sample test and one parallel analysis using orthogonalized uncertainty measures. Our out-of-sample test is done by using an expanding window in estimating the index weights used to predict future excess returns. On a stand alone basis, we find that our uncertainty measures perform well out-of-sample, with strong statistical significance. However, once we control for the forward factors from Cochrane and Piazzesi (2005), we do find positive performance but with low statistical significance. The second robustness test is performed due to a puzzling correlation structure between our uncertainty measures, with high positive correlation between the good and bad uncertainties. Due to this and to ensure that our results are not biased, we force the correlation to zero between the uncertainty proxies. Using these uncorrelated proxies, both on individual variable regressions and on index-level regressions, we find no strong indications that our results are influenced by the positive correlation between our measures.

We proceed as follows. In Section II, we review the relevant literature to our research. In Section III, we present our data and the construction of our uncertainty measures and in Section IV we put forward the economic intuition behind our hypotheses. The empirical investigation is carried out in Section V, followed by our out-of-sample tests in Section VI. Lastly, we draw important conclusions and make suggestions for future research in Section VII.

II. Review of Literature

Our research is related to two strands of literature. On the one hand, we contribute to the broad literature concerning bond return predictability and on the other hand, we add onto a growing body of research focusing on economic uncertainty and its impact on output and asset prices. Firstly, there is a voluminous body of research concerning the predictability of excess bond returns. The early strand of the literature focused mainly on the Expectation Hypothesis and how forward rates along the yield curve contained information regarding future returns. Two famous examples of this are Fama and Bliss (1987) and Campbell and Shiller (1991), which both found evidence of return predictability and a time variation in expected excess returns. Continuing on the notion of predictability from financial factors, Cochrane and Piazzesi (2005) documented five forward factors along the yield curve and found evidence that these captured roughly 40 percent of the variation in future excess returns. There are several other studies investigating the same issue, but our paper is more closely related to a growing body of research investigating the impact of macroeconomic risks on the risk premia of bonds. A seminal paper in this field, written by Ludvigson and Ng (2009), used a broad set of macroeconomic variables. After using a dynamic factor analysis, they found high explanatory power of their estimated factors, capturing around 20 percent of the variation in future excess return. The results were especially robust for factors loading strongly on either real aggregates, such as unemployment, GDP and consumption, or on inflation. More importantly, they documented that macroeconomic factors help to explain risk premia over and above the information contained in the yield curve. Consequently, they concluded that macroeconomic risks are important to understand bond risk premia. Adding to this, they also documented a substantial countercyclical component in excess returns, something also found by Wachter (2006). She derived a consumption based asset pricing model inspired by Campbell and Cochrane (1999), in which she explained the countercyclical component in excess returns through a moving risk aversion which is high in bad states and low in good states.

Secondly, since the Great Recession, the interest in the implications of economic uncertainty has gained traction. This field of research, both theoretical and empirical, is still in its early stage and there is no conclusive view on how one should quantify uncertainty. The most common way is to use the volatility of the residuals in some auto regressive process. For example, Bali, Brown, and Caglayan (2014) employed a GARCH model to estimate the residuals when investigating hedge fund exposure to macroeconomic uncertainty. Similarly, Bansal and Shaliastovich (2013) used a VAR(1) model when investigating the impact of real and inflation uncertainty on bond risk premia. Recently, Ludvigson et al. (2015) documented that most proxies for uncertainties actually capture other aspects than true *macroeconomic uncertainty*. Consequently, they developed a broader measure of uncertainty from more than 130 macroeconomic variables and found evidence that such measure was more persistent, more extreme but had much fewer episodes of elevated uncertainty compared to other proxies. Nevertheless, when those periods occurred, their measure exhibited higher correlation to real economic activity. Although this strand of literature is new, the papers focusing on separation of good and bad movements are even fewer.

Recently, Bekaert, Engstrom, and Ermolov (2016) started from a model in which supply and demand shocks can be characterized as either good or bad. They found evidence that this separation can help explain some of the turmoil of the Great Moderation. Further, using good and bad structural shocks, they indicate that macroeconomic risks indeed contribute to time-variation in bond risk premia and that risk premia is countercyclical. Related to the decomposition of good and bad movements, Barndorff-Nielsen, Kinnebrock, and Shephard (2008) presented evidence which indicates that semi-variances are informative about the risks in the tails of the underlying distribution. Shaliastovich and Mete (2015) used this finding to separate good and bad components in the variance premium when investigating the predictability of excess return in stocks.

Perhaps most importantly, our benchmark paper by Segal et al. (2014) starts from the same notion. In their paper, they start from the Long-Run Risk Model by Bansal and Yaron (2004), which they extend by including two zero-mean shocks to consumption, which respectively captures positive and negative innovations to consumption. The volatility of the shocks are derived from the semi-variances of various macroeconomic variables. Accordingly, positive semi-variance implies good uncertainty, which drives positive innovations to consumption. The same holds for the negative semi-variance but for negative innovations to consumption. They found that good (bad) uncertainty predicts increased (decreased) economic activity. They also documented that the uncertainty measures are priced in the cross section of stocks and that both contribute to an increased risk premia. Our empirical investigation start from this paper.

III. Data

A. *Macroeconomic Data*

The quarterly macroeconomic data of individual forecasts is sourced from the Survey of Professional Forecasters (SPF) at the Federal Reserve Bank of Philadelphia. This is a database of professional estimates on the overall health and growth of the U.S. economy. As pointed out by Eriksen (2015), such data set is ideal in predicting excess bond returns as SPF data is model-free, available in real-time and is not subject to revisions. All these features should make the latent factor, common in macroeconomic data, minimal. However, the data also comes with some issues. Namely that respondents might give strategic rather than believed estimates, which would impose a issue in our construction of uncertainty proxies as they will appear biased. Nevertheless, the SPF started in Q4 1968 and was first conducted by the American Statistical Association and the National Bureau of Economic Research (NBER) but responsibility of the survey was assumed by the Philadelphia Fed in the 1990s[1]. The surveys are sent out to large corporations, Wall Street firms, economic consultancy firms and university research centers in the second month of each quarter. For example, in the latest survey of our data set, the majority of the responses came from either economic consultancy firms or financial services firms. The respondents leave forecasts on a range of different macroeconomic variables for each quarter from the current one up until one year ahead. In this paper, we use the forecasts that are made for one year ahead. Following evidence from Ludvigson and Ng (2009) and Bansal and Shaliastovich (2013), we focus on real and inflation variables such as Real GDP, Real Personal Consumption Expenditures, and Inflation. For Real GDP and Real Personal Consumption, forecasts are given in level estimates while Inflation is given in percentage changes. Consequently, we have to transform the two former forecast variables to also be expressed in percentage changes.

$$\Delta y_t^i = log\left(\frac{y_{t+1}^i}{y_t}\right) \tag{1}$$

This is done by taking the log growth rate of the level estimate, y, made by agent i for time $t+1$, over the now-cast value of the same variable in time t. This transformation ensures that we obtain individual growth rate estimates for both Real GDP and Real Personal Consumption. To minimize the impact of extreme estimates, we eliminate the maximum and minimum forecasts within each quarter for all variables.

[1]For more information on SPF data and documentation, please consult the website of the Federal Reserve Bank of Philadelphia.

Table I: Summary Macroeconomic SPF Data

Macroeconomic Indicator	Notation	Start Date	End Date
Real GDP	RGDP	Q4 1974	Q4 2016
Real Personal Consumption	RCONS	Q3 1981	Q4 2016
Inflation	CPI	Q3 1981	Q4 2016

Note: This table shows the summary, notation and sample period that are used in the rest of the paper.

In the early years of the forecast history, there was low consistency in the average number of respondents. Due to the high variation and often missing data for the annual forecast, we start our analysis in Q4 1974 for data on RGDP. As for RCONS and CPI, we start our analysis in Q3 1981. This is also due to data availability and quality. In Table I we present a brief overview of our notation and sample period by variable. In addition to the forecast data used, we obtain data on realized industrial production growth from the Federal Reserve Bank of St. Louis and aggregate macroeconomic uncertainty from the personal website of Sydney C. Ludvigson[2].

B. Bond Data

When it comes to the data on bond excess returns, we use the Fama-Bliss data set provided by the Center for Research in Security Prices (CRSP). The data includes discount prices on U.S. treasury bonds with maturities ranging from 1 to 5 years. The data is provided on a monthly basis so we construct quarterly prices by matching the dates to those in our SPF data set. This implies that on each date that we have an annual forecast made by N agents, we also have discount bond prices. We have used a different data set provided by Gürkaynak, Brian, and Wright (2006) to validate the bulk of our findings and the results are qualitatively the same. The final data set, depending on start date, have between 169 to 142 quarters of data on bond prices and macroeconomic forecasts.

$$rx_{t\to t+m}^{(n)} = p_{t+m}^{(n-m)} - p_t^{(n)} - y_t^m \tag{2}$$

$$f_t^{(n)} = p_t^{(n-m)} - p_t^{(n)} \tag{3}$$

[2]Retrieved from Sydney C. Ludvigson personal website on March 14, 2017.

In constructing excess bond returns and forward rates, we follow the notation by Cochrane and Piazzesi (2005)[3]. The excess return at $t + m$ on a n year discount bond, held for m years and the m-year log forward rate is given in the equations above. In our empirical analysis, we set m to 1 year.

C. Descriptive Statistics

Based on data from the Bureau of Economic Analysis tables, the realized average annual growth in RGDP over our time period amounts to roughly 2.77 percent, while RCONS had an average annual growth of 2.35 percent. Furthermore, the Bureau of Labor Statistics indicates that the average realized annual inflation rate was 3.03 percent during our time sample for CPI. In Appendix A, Table XIII, we display the relevant descriptive statistics for the SPF data on a yearly basis. We observe averages for both RGDP and RCONS slightly higher than their realized counterparts, while CPI almost matches the realized inflation over the time period. We can therefore conclude that our forecast data is a reasonable good fit to actual data. One advantage of the yearly overview is the ability to show the standard deviation of the forecasts and the most optimistic and pessimistic estimates by year. For all variables, the standard deviation of the estimates was high up until mid to early 1980s, indicating low agreement between the respondents which is consistent with the business cycle volatility being high during this time. We can also see the immediate impact of the Great Recession on RGDP and RCONS, especially in the variation of the responses and the most pessimistic forecasts. Lastly, notice the number of respondents being relatively stable around 140 per year, or around 35 respondents per quarter, from the beginning of the 1990s. Proceeding to the bond data, Table II, displays the average excess bond returns. We show a monotonically increasing pattern in excess returns in the maturity of the bonds. This, along with the same pattern in standard deviation, is expected as holders of longer maturity bonds are compensated for carrying a higher interest rate risk.

[3] The log bond price is given by $p_t^{(n)} = log\left[P_t^{(n)}\right]$ and the log yield is given by $y_t^{(n)} = -\frac{1}{n}\left[p_t^{(n)}\right]$.

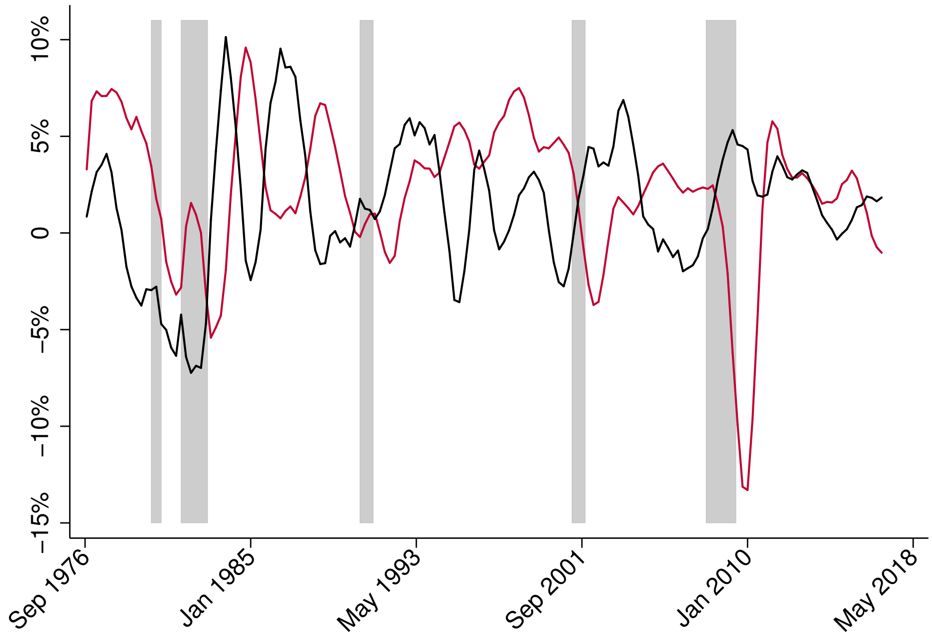
Table II: Excess Bond Returns

		$rx^{(2)}$	$rx^{(3)}$	$rx^{(4)}$	$rx^{(5)}$	$\overline{rx}$
Panel A 1974Q4	**Average**	0.77	1.24	1.75	2.00	1.43
	Max	5.97	10.26	14.38	16.89	11.44
	Min	–5.56	–9.56	–12.85	–17.55	–10.07
	Std.	1.79	3.30	4.78	5.95	3.95
Panel B 1981Q3	**Average**	1.00	1.86	2.63	3.10	2.15
	Max	5.97	10.26	14.38	16.89	11.44
	Min	–2.37	–5.25	–7.08	–8.51	–5.73
	Std.	1.56	2.96	4.22	5.21	3.45

Note: This table shows the descriptive statistics of the excess bond returns. All numbers are in percent. Panel A gives numbers covering 166 quarters from 1974 Q4 to 2016 Q4 and Panel B a sample of 139 quarters from 1981 Q3 to 2016 Q4.

In Panel A, the Sharpe ratio goes from 0.43 for the 1 year bond to 0.34 for the 5 year bond. Our portfolio across all maturities yields a Sharpe ratio of 0.36. We can therefore confirm the commonly documented declining Sharpe ratio in maturity of nominal bonds. For Panel B, the numbers are higher, yielding a Sharpe ratio for the average excess return portfolio of 0.62. Since the staring year between the two panels only differs by roughly seven years, it is of interest to plot the average excess bond returns through time. In Figure 1 we display the moving average of annual excess return across all maturities and the corresponding realized growth in industrial production. The correlation between the two series amounts to -0.20 and if we exclude the period before the Great Moderation, the correlation is -0.40. Arguably, this could indicate a countercyclical component in excess bond returns and is something discussed in several papers (see, e.g. Ludvigson and Ng (2009), Wachter (2006), Eriksen (2015)). The most striking feature of the graph is the period post the mid-1980s, where each time industrial production growth is at its bottom, average excess returns is as its peak.

Figure 1: Average Excess Returns and Industrial Production Growth



Note: This graph displays the moving average of the average yearly excess bond returns (black line) and the corresponding moving average of yearly industrial production growth (red line). The moving average process is applied on the 4 latest quarters, MA(4). The data is quarterly between Q4 1974 and Q4 2016. Dark grey shaded areas are U.S. recessions as defined by NBER.

This discussion, however, does not give an answer to the question why average returns between Panel A and B in Table II differ. The steep decline in excess returns during the end of the 1970s and the beginning of the 1980s marks the beginning of the Great Moderation. This period was characterized by a high positive correlation between economic activity and excess returns, which is contrary to the following period. In this transition, the U.S. economy experienced low growth, high inflation and high interest rates. Bekaert et al. (2016) find evidence that reduction in business cycle volatility is mostly due to the decrease of the positive skewness of demand shocks. They define demand shocks as episodes that move real economic activity and inflation in the same direction, common in both recession and boom periods. Furthermore, the big decrease in excess returns of the early 1980s coincides with a period in which Bekaert et al. (2016) finds large negative demand shocks to the economy.

D. Construction of Uncertainty Measures

Generally, uncertainty is defined as the conditional volatility of the residuals that stems from the error in the forecasts made by economic agents (Ludvigson et al. (2015)). There are various ways to construct uncertainty measures, but most methods seek to remove the predictive component in the time series. Many scholars use GARCH or VAR models to estimate the conditional volatility of the forecast errors (see, e.g., Bali et al. (2014), Bansal and Shaliastovich (2013) and Ludvigson et al. (2015)). This methodology is suitable if analyzing aggregate uncertainty, but it imposes econometric issues in separating good and bad uncertainties components. We do as Segal et al. (2014) and follow the method proposed by Barndorff-Nielsen et al. (2008) in the usage of semi-variances. In this setting, positive and negative semi-variances ought to be informative about movements in the right and the left tail of the underlying distribution. This alters the fundamental notion of the construction of uncertainty proxies as we do not have the need of removing the predictive component but simply focus solely on such component. As the nature of the SPF data is to only have a predictive component, we utilize the power of this feature and therefore circumvent the need of estimating any structure in the data. Adding to this, recent evidence indicates that survey data uncertainty can be approximated through the cross sectional dispersion of individual estimates (Della Corte and Krecetovs (2015)). Thus, by using this cross sectional dispersion along with the semi-variances, we find our foundation for uncertainty construction to be consistent with previous research. To enable us to use semi-variances, we derive a demeaned version of Δy, for all macroeconomic indicators[4].

$$V_{j,t}^{Neg} = \frac{1}{N} \sum_{i=1}^{N} \mid (\Delta y_{j,t}^{i} < 0)\ \Delta y_{j,t}^{i^2} \tag{4}$$

$$V_{j,t}^{Pos} = \frac{1}{N} \sum_{i=1}^{N} \mid (\Delta y_{j,t}^{i} \geq 0)\ \Delta y_{j,t}^{i^2} \tag{5}$$

$$V_{j,t}^{Tot} = V_{j,t}^{Neg} + V_{j,t}^{Pos} = \frac{1}{N} \sum_{i=1}^{N} \Delta y_{j,t}^{i^2} \tag{6}$$

[4]The difference between using the conditional mean or the conditional median is negligible. The structure of the semi-variances are practically the same.

In the equations above, the $|(\cdot)$ represents an indicator function. Thus, $V_{j,t}^{Neg}$ is the negative semi-variance, capturing all estimates made by agent i falling below the quarterly mean in quarter t, for the macroeconomic variable j. Accordingly, $V_{j,t}^{Neg}$ should be informative about the expectations in the left tail. Equivalently, the positive semi-variance captures the estimates that are above the conditional mean and is therefore informative about the right tail of the expectations. By construction, the sum of the two semi-variances gives the total variance, $V_{j,t}^{Tot}$. As noted, compared to Segal et al. (2014), we do not have the need of projecting the future semi-variance as our data already is forward looking and only contains predictive components. Thus, the Equations (4) through (6) make the foundation of the uncertainty measures we use in the rest of this paper.

However, as positive semi-variance does not necessarily imply good uncertainty and vice versa, negative semi-variance does not necessarily imply bad uncertainty, it is of value to discuss these measures before proceeding with the analysis. Thus, one has to be careful regarding the economic meaning of each variable and the left and right tail of the distribution of the specific variable. Consequently, right tail forecasts for RGDP and right tail forecasts for CPI will not by construction have the same economic interpretation. However, for RGDP and RCONS, $V_{j,t}^{Pos}$ coincides with good uncertainty. The reason for this is that when we have high positive semi-variance in these variables, economic agents are uncertain in *how good can the economic climate be in one year*. This follows from the notion that high variance in the right tail implies high dispersion in the forecasts made above the conditional mean. Using common sense, it is not hard to see that estimates above the mean for these variables are good for the economy. If consumer spending is estimated to be high or GDP is projected to increase, we can infer that agents expect favorable conditions in the future, with high production, employment and other beneficial economic circumstances. Accordingly, we label $V_{j,t}^{Pos}$ as $UNC_{j,t}^{Good}$ and $V_{j,t}^{Neg}$ as $UNC_{j,t}^{Bad}$, where $j = \{RGDP, RCONS\}$ and capture the uncertainty in t about variable realization in $t+1$.

For CPI, however, V_t^{Pos} is bad for the economy. Based on findings by Piazzesi and Schneider (2006), we know that excessively high inflation hurts the real economy. This is something modeled by Bansal and Shaliastovich (2013) in their version of a Long-Run Risk Model. The underlying idea in this setting is that excessive inflation forces economic agents to shift their behavior to cover up the loss in real income. We build on this and therefore, label high positive semi-variance in CPI as indication of high bad uncertainty as it is negative for the real economy. Effectively, agents are uncertain how much their consumption behavior needs to change, which drives uncertainty in *how bad can the economic climate be in one year*. Thus, for CPI, V_t^{Pos} is UNC_t^{Bad} and V_t^{Neg} is UNC_t^{Good} which captures the uncertainty in t about inflation realization in $t+1$.

In Appendix B, we display the time variation in all uncertainty measures used in this paper. As discussed earlier, the transition into the Great Moderation is evident in virtually all uncertainty measures. We see high uncertainty up until the mid 1980s, consistently with the overall decline in the business cycle volatility after this period. We also see uncertainty measures spiking during the Great Recession. This pattern of uncertainty is fairly similar to patterns reported by Segal et al. (2014). Furthermore, this pattern in the uncertainty measures is also confirmed by Ludvigson et al. (2015), although they document that the highest peak in uncertainty occurred in the recent financial crisis. Worth noticing is that they investigate a broader set of macroeconomic indicators and a different econometric framework. In Table III we display the correlation between all our uncertainty measures.

Table III: Correlation Matrix Between Uncertainty Measures

	$RGDP^{Good}$	$RCONS^{Good}$	CPI^{Bad}	$RGDP^{Bad}$	$RCONS^{Bad}$	CPI^{Good}
$RGDP^{Good}$	1.00					
$RCONS^{Good}$	0.49	1.00				
CPI^{Bad}	0.63	0.46	1.00			
$RGDP^{Bad}$	0.66	0.63	0.82	1.00		
$RCONS^{Bad}$	0.61	0.66	0.52	0.67	1.00	
CPI^{Good}	0.60	0.32	0.70	0.60	0.44	1.00

Note: This table shows the correlation structure of our uncertainty measures. For ease of readability, we have dropped the *UNC* notation. The sample is quarterly from Q3 1981 to Q4 2016

One issue is that we are unable to clearly separate good and bad uncertainties in the same underlying variable, which all are in the region of 0.65 to 0.70. Although Segal et al. (2014) only investigate one uncertainty variable, they also find a high positive correlation of around 0.50 between good and bad uncertainty. However, as we hypothesize polarized effects of high good and high bad uncertainties, we do find it troublesome to observe such high positive correlation. Consequently, we try to correct for this issue by running a parallel analysis using an orthogonalized version of the variables and thereby forcing the correlation to zero. Accordingly, we regress good uncertainty on bad uncertainty and use the residuals from such regression as a new variable for good uncertainty. The new variable will, by construction, have zero correlation to the bad uncertainty and thus, give us a second view on the importance of both good and bad uncertainty measures with respect to bond risk premia[5].

Besides these issues, we do find some interesting correlations. The most striking correlation is the one between the bad uncertainty about RGDP and the bad uncertainty about CPI of 0.82. This in line with evidence on the non-neutral impact high inflation has on the real activity of the economy (see, eg., Bansal and Shaliastovich (2013) and Piazzesi and Schneider (2006)). Thus, we see that our uncertainty measures do contain information already confirmed by other scholars. Furthermore, if we disregard the time period before 1990, correlations fall, although not to the levels of Segal et al. (2014) and definitely not to single digit correlations. Also, even tough not displayed to save space, we can confirm the finding that all bad uncertainties correlates with the corresponding aggregate uncertainty to a higher degree than the good counterpart.

IV. Empirical Predictions

Our empirical analysis and tests rest upon the insights from the model provided by Segal et al. (2014). As described, within the model there are positive and negative shocks to consumption that are driven by good and bad uncertainty respectively. Our predictions are based on the economic notion that agents want to have as high utility as possible in all states of the world. Accordingly, when consumption is low and their utility from consumption decreases, they would like to own assets which have high payoff at exactly those times, so that their utility from financial wealth would increase. In the end, this would give a neutralized effect on their overall well-being. As noted previously, several

[5] We will present the quantitative results of such a parallel analysis in an Online Appendix and discuss the qualitative importance for these results in the sections to come.

scholars have documented a countercyclical component in bond risk premia. Based on this, we have a framework which indicates that bonds indeed have high returns when economic activity is low. This was something we briefly discussed in Section III.C regarding Figure 1, where we clearly saw excess bond returns spiking in each episode industrial production plummeted.

The first prediction we make, as done by Segal et al. (2014), is that high good (bad) uncertainty should predict increased (decreased) economic activity. This follows from the underlying model and the economic intuition, which states that high good (bad) uncertainty drives higher (lower) growth in consumption. Thus, if consumption growth is high (low), economic activity should be high (low) to meet aggregate demand. As we proxy economic activity by the growth in industrial production, we investigate the effect of a shock to aggregate demand, onto a proxy of aggregate supply. In reality this can take many forms. One potential expression of high good (bad) uncertainty is that producers see high (low) aggregate demand going forward and therefore, increase (decrease) their production to serve this change in demand. One evident issue in this setting is causality. This stems from the fact that we do not provide a theoretical model for our notion, which implies that we cannot validate the causality of any shock or shed light on what might initiate any macroeconomic uncertainty. Although it is of great value to understand this dynamic and the drivers behind demand and supply shocks, it lies outside the scope of this paper.

Albeit not explicitly, we do rely on evidence of a countercyclical risk premia in bonds to make our excess return predictions. Using economic theory and intuition, we can deduce the following: if high bad uncertainty is related to low economic activity as indicated by the model, there will be an increased demand for assets with negative comovement with economic activity. The reason for this is that assets with positive comovement will be more negatively affected when aggregate demand or economic activity falls. Intuitively, if economic agents see bad uncertainty regarding the future economic state of the world, they want to own assets that give them high payoffs in these states, which goes back to the discussion on the goal of keeping well-being high. Similarly, if agents see good uncertainty about the future economic state, there are no incentives for owning assets that give them insurance against bad times. Consequently, in the wake of high good (bad) uncertainty, future excess bond returns should decrease (increase). This would imply that high bad uncertainty on average would contribute negatively to risk premia as agents would be willing to pay a premium for assets that have a negative correlation with consumption. Equivalently, good uncertainty would on average contribute positively to risk premia as this increases the risk of seeing low return in times of low economic activity. By linking real economic activity and future excess returns to good and bad uncertainties, we strive to provide a potential explanation for the countercyclical component in bond risk premia.

V. Empirical Analysis

The main purpose of the following sections is to empirically validate and investigate the predictions made. Firstly, in Subsection V.A we analyze the variable-level relationships between our measures of aggregate, good and bad uncertainty and bond risk premia. We use a set of predictive regressions to empirically test any relationship and to observe whether decomposing uncertainty into good and bad components improves the predictive ability of our uncertainty measures. We also put forward the economic intuition for how the uncertainty measures relate to future excess returns. This section is important as we need to validate our hypotheses in order to proceed with the main analysis. Secondly, in Subsections V.B.1 and V.B.2 we introduce three indices of general macroeconomic uncertainty built using weights derived from a Principal Component Analysis (PCA). We replicate the predictive analysis executed on individual variables to observe a more general relationship between macroeconomic uncertainty and bond risk premia. Thirdly, in Subsection V.B.3, we try to confirm the channel from the uncertainty indices to the business cycle using realized industrial production growth as a proxy for economic activity. Our intent is to link good and bad macroeconomic uncertainty, bond risk premia and the state of the business cycle within the same spiral. Fourthly, in Subsections V.B.4 and V.B.5 we validate our findings concerning the predictive ability of our uncertainty measures by controlling for commonly documented financial and macroeconomic factors. Fifthly, in Subsection V.C we check whether we are able to confirm the evidence from Segal et al. (2014) that good (bad) uncertainty has a positive (negative) price of risk using the framework from Fama and MacBeth (1973). Lastly, in Section VI, we perform out-of-sample tests to assess the robustness and consistency of our findings.

Before proceeding with the empirical analysis, we raise a technical note. Working with macroeconomic data and an overlapping return structure, the autocorrelation and heteroskedasticity in the error terms impose an issue in the regressions. That is, the analysis might understate the standard errors and can therefore lead to biased results. One way of overcoming this issue is to use the method proposed by Newey and West (1987) in estimating the covariance matrix. However, this entails setting a lag-length in order to cope with the autocorrelation in the residuals. There are no, or few, explicit ways in determining such number, but Green (2003) indicates that the number of lags in the Newey-West standard errors estimation can be approximated through $L = N^{1/4}$, where N is the number of observations. Using this approximation yields a rough lag length of four. This is what we use for all our regressions in the upcoming sections.

A. Predictive Analysis

As a first step in our empirical analysis, we use our proxy measures of macroeconomic uncertainty to test their predictive power with respect to future excess bond returns. To do so, we regress excess bond returns for all maturities onto our uncertainty measures of each macroeconomic variable separately. We also test the average predictive power using an equally weighted portfolio across all maturities. We run the following regressions:

$$rx^{(n)}_{t\to t+1} = const + \beta^{(n)} UNC^{Agg}_{j,t} + error \tag{7}$$

$$rx^{(n)}_{t\to t+1} = const + \beta^{(n)}_{g} UNC^{Good}_{j,t} + \beta^{(n)}_{b} UNC^{Bad}_{j,t} + error \tag{8}$$

where $j = \{RGDP, RCONS, CPI\}$ and n indicates the maturity of the bond. The reason for us to run these two specification is twofold. Firstly, we need to validate the sign for all loadings across both specification and secondly, to asses whether the decomposition increase the explanatory value as measured by the R^2.

To build the intuition behind our expectations, it is useful to discuss the economic meaning of our uncertainty measures and how we relate them to future excess returns. Due to the economic meaning of each separate variable, we have stressed the importance of making a difference between right and left tail compared to good and bad uncertainty. Refraining from being repetitive, we will not go over the definition again but more explicitly lay out the implications of good and bad uncertainties with respect to future excess returns. Starting with good uncertainty, which indicate that investors expect economic aggregates to come in favorable in the following year[6]. Building on evidence from Wachter (2006), we know that in times of economic expansion, risk aversion tends to decrease. Accordingly, if we see high good uncertainty, risk aversion is likely to decrease and therefore, it is more likely that investors will shift capital allocation to risky assets. Turning the argument around, in the wake of high bad uncertainty, investors are more pessimistic. Equivalently, bad uncertainty will start to increase the risk aversion and investors would seek assets that see lower risk of losing value in order to limit their downside risk. In this setting, there will be a demand effect in treasuries that would drive up the excess returns. Consequently, we would expect future excess returns, across all individual specifications, to have a positive beta with respect to bad uncertainty while the opposite should be true for good uncertainty. We argue that this decomposition yields a more informative approach in predicting excess returns than using aggregate uncertainty measures.

Based on empirical evidence and the theoretical model from Segal et al. (2014), we see that measuring dispersion on a relative basis from the conditional mean provides additional value. The reason for this is that it is only natural for agents to disagree on which direction the economy is heading, but if we are able to tease out the direction of this uncertainty, we will enhance our ability to predict how asset prices might react. This is not possible to do if we take the more common approach and use aggregate uncertainty. Consequently, we expect the specification of aggregate uncertainty measures to consistently deliver lower explanatory value than our decomposed specification of uncertainty measures. Our expectations on the aggregate uncertainty loadings are formed by previous findings by Bansal and Shaliastovich (2013) and our discussion of the fundamental notion of uncertainty for each variable. This implies that the regressions using aggregate uncertainty becomes more of a confirmation test. That is, high aggregate uncertainty in CPI should generate a positive loading while the real variables would give negative loadings. These expectations are based on the non-neutral effect of excessive inflation and the notion of favorable implication of real aggregates.

In Appendix A, Tables VII, VIII and IX illustrates the coefficients, Newey-West stan-

[6]Please see our discussion under Section III.D where we constructed our uncertainty measures for a more deliberate discussion of this.

dard errors and R^2 of the regressions. As discussed, we have found a relatively high correlation between our uncertainty measures across each of our macroeconomic variables. In a multiple regression specification, this might complicate the assessment of the significance on the individual loadings. Thus, in the last row of each table we report the p-value of a Wald Test for the joint significance of good and bad uncertainty. In most cases we are able to reject the hypothesis that the coefficients of the uncertainty measures are jointly zero. In particular, the p-values are below 1 percent for CPI uncertainty measures, lower than 5 percent for RGDP uncertainty measures and less than 10 percent for RCONS uncertainty measures.

Across all the three macroeconomic variables, we find consistent empirical evidence in favour of our predictions and expectations. That is, we find positive (negative) slope coefficients for bad (good) uncertainty measures across all variables. The loadings are economically large and, in some parts, statistically significant. It is important to highlight that the size of the loadings is influenced by the fact that our right-hand side variables are expressed in variances. Nevertheless, the loadings are indeed large, something documented by Segal et al. (2014) as well. As these regressions are performed variable by variable, there is potentially a high degree of noise in the estimates of uncertainty. Going back to the underlying model, the uncertainty measures drive shocks to consumption. Thus, if the uncertainty measures give a low information value, the actual impact on the link to future changes in consumption will be lower. Not surprisingly, this would weaken the channel to future excess returns. Such effect can be observed on the loadings and our inability to generate simultaneous significance across good and bad coefficients. We will adjust for this issue in later sections where we construct index weights with the goal of refining and capturing more information regarding good and bad uncertainty.

As previously mentioned, we execute a parallel analysis of the uncorrelated uncertainty measures constructed using an orthogonalization process. We perform the same predictive regressions with uncertainty measures that are uncorrelated by construction. Please find the empirical results of this analysis in our Online Appendix. Notice that our initial specifications were not rejected due to excessive collinearity. Despite this, we still see that this parallel analysis provides value as the correlation structure might have implications for the respective loadings on good and bad uncertainty. Starting with RGDP, we see good uncertainty being virtually unchanged, despite the fact that the good uncertainty is completely transformed. Bad uncertainty, however, has lost its significance on the short term maturities. Furthermore, we see sign switches in bad uncertainty, which contradicts our underlying expectation. As for RCONS, there are no to very small changes across the two uncertainty measures. The only difference we find is that the loading on bad uncertainty somewhat decreases but maintains its significance. Lastly, for CPI we find unchanged loadings on bad uncertainty. For good uncertainty, we see sign changes across all maturities, although being statistically insignificant at longer maturities. This is the most troublesome results if we consider our predictions as the short term bonds see sign changes and high statistical significance for good uncertainty. Notice that CPI was the variable that had the highest positive correlation between good and bad uncertainties. Thus, it does look like our initial results for CPI, at least to some part, were driven by a suspicious correlation. Taken together, however, we argue that we cannot make any powerful rulings from these results. The reason for this is that the loadings that previously were insignificant keep on displaying the same behavior and vice versa for our significant loadings. Accordingly, our previous results which indicated that our underlying notion held are still intact. However, for us to be able to make stronger statements, we need to reduce the noise in the uncertainty proxies, something pursued in later sections.

The empirical results from the individual regression supports the intuition that decomposing aggregate uncertainty into its good and bad component yields higher explanatory power as measured by the R^2. We observe an improvement of at least 5 percent when comparing the regressions using UNC_j^{Agg} with the regressions using the two factors UNC_j^{Bad} and UNC_j^{Good}[7]. Arguably more interesting is the fact that the bad uncertainty loadings tends to be larger (in absolute terms) compared to the good uncertainties, with the exception in the RGDP specification, and more statistically significant. Also, bad uncertainty loadings tends to be larger compared to aggregate uncertainty. This is interesting as bad uncertainty is predicted to have a positive impact on future excess returns. While striking, this is a secondary result and not the core of our analysis. We do, however, see value in discussing this evidence from a qualitative perspective. One potential explanation could be that investors dislike bad states of the world disproportionately to how

[7]Note that while we show simple R^2, we observe substantial increases in the predictive ability even when using $adjusted-R^2$ and the difference is negligible.

they enjoy good states. Accordingly, our results line up with the discussion put forward by Tversky and Kahneman (1992) and in particular, with the concept of loss aversion. We have argued that investors derive utility from consumption and also from their financial wealth. Using the concept of loss aversion, investors would be more sensitive to decreases than to increases in their financial wealth. Consequently, all else equal, investors would react more to a scenario where they expect bad economic conditions, than in the opposite case. Not surprisingly, in the wake of bad uncertainty, investors would seek asset allocations that protect them from decreases in financial wealth. Thus, given the same level of uncertainty in absolute terms, we would expect the capital inflow in bonds to be larger in a case with high bad uncertainty than the capital outflow in a high good uncertainty state. This stems from the notion that bonds ought to have lower comovement with overall economic activity compared to stocks and would explain the asymmetric impact of the two uncertainty components on bond risk premia. This reasoning does however raise the need for further analysis. More specifically, the need of establishing the link between of our uncertainty measures to the real economy, something pursued in later sections.

B. Uncertainty Index Analysis

Working with multiple macroeconomic indicators, using factor analysis is a suitable tool to extract the common variation among correlated factors such as the one used in our previous analysis. One potential methodology to use is Principal Component Analysis (PCA), which simply is a transformation to reduce the dimension of the data. The method does not assume that the data follows any particular statistical model. We are in good company as many other researchers follow the same method in similar studies. We are motivated to pursue a PCA based on our findings under the individual regressions. We hypothesized a high degree of noise in the uncertainty measures, which potentially could be reduced using a PCA therefore improving the predictive power of such measures.

B.1. Methodology and Construction

The goal of our PCA is to build two separate broad indices of macroeconomic uncertainty. We use two sets of uncertainty measures time series: one set will be made of the three $UNC_{j,t}^{Bad}$ time series and the other will be derived from the three $UNC_{j,t}^{Good}$ time series.

Where j represents the individual macroeconomic variables used in this paper. Note that PCA requires time series of equal length, we thus use data starting from Q3 1981 for each of the three macroeconomic variables. Using the underlying foundation of the model from Segal et al. (2014), we argue that we should be able to reduce the noise by constructing these indices and thereby refining our predictive signals. First of all, we run two separate PCA on the two sets of time series. The output from such analysis is a set of three eigenvectors, representing the loadings of each uncertainty measure in the first, second and third principal component, and three eigenvalues. Each of such values are directly associated with one of the eigenvectors, with the highest eigenvalue corresponding to the first principal component eigenvector, and so on. It is common practice in a PCA to consider only the eigenvectors associated with eigenvalues higher than one, which leads us to consider only the first principal component in both the bad and good time series. This is beneficial as the first component has the interpretation of being the linear combination that explains the most variance in the data (Bali et al. (2014)). To support such decision, we observe that the first principal component explains approximately 65 percent of the variation of the data in the good PCA, 78 percent in the bad specification and finally, that the incremental power of the following components decreases vastly. Using the loadings in for the first component yields the following expression for the two indices:

$$PCA_t^{Good} = 0.6496 * UNC_{RGDP,t}^{Good} + 0.5191 * UNC_{RCONS,t}^{Good} + 0.5744 * UNC_{CPI,t}^{Good} \quad (9)$$

$$PCA_t^{Bad} = 0.6175 * UNC_{RGDP,t}^{Bad} + 0.5306 * UNC_{RCONS,t}^{Bad} + 0.5807 * UNC_{CPI,t}^{Bad} \quad (10)$$

This enables us to use the two indices in a regression analysis similar to the one in Section V.A to predict future excess returns. We can see that both indices load quite evenly across the three variables, indicating that all variables are equally relevant in understanding our respective uncertainty indices. Importantly, while the direct relationship and intuition between each single macroeconomic variable and risk premia diminishes; using the two indices is beneficial in order to understand whether reducing the data help in refining the predictive signals. Ideally, this will help us in better understanding future excess returns and the potential link between macroeconomic uncertainty and economic activity. Also, having condensed the structure of the data with respect to bond risk premia in just two factors, it is easier to control whether our methodology and uncertainty measures enables us to explain risk premia over and above both financial and macroeconomic factors. Note that, following the same methodology illustrated above, we also build the index PCA_t^{Agg} using aggregate uncertainty for each variable. This index exhibits the same characteristics as the two other indices. That is, we see a first principal component explaining roughly 60 percent of the total variation in the data and the index loads evenly across all uncertainty measures. Throughout the rest of the paper, we will use such aggregate index as a benchmark to observe whether decomposing uncertainty adds value to our analysis by providing more significant and insightful results.

B.2. Predictive Analysis Pt. II

Following the same methodology used in Section V.A, we regress future excess returns onto our newly constructed uncertainty indices. It is of interest to run such regressions for two reasons. Firstly, to observe whether the positive (negative) slope coefficient of bad (good) uncertainty with respect to bond risk premia are preserved. Here, we do not expect different outcomes compared to the other predictive regressions used so far as no fundamental implication of the data is transformed. We do however expect increased significance on the loadings due to the potential reduction of noise in the uncertainty signals. Secondly, to measure how large the combined predictive power of the indices are. Once again, due to the potential reduction of noise, the explanatory power should increase. Additionally, we use PCA_t^{Agg} to run a second regression to maintain a comparable benchmark in the evaluation of how much value the decomposition of good and bad uncertainty provides. We run the following regressions:

$$rx_{t\to t+1}^{(n)} = const + \beta^{(n)} PCA_t^{Agg} + error \tag{11}$$

$$rx_{t\to t+1}^{(n)} = const + \beta_g^{(n)} PCA_t^{Good} + \beta_b^{(n)} PCA_t^{Bad} + error \tag{12}$$

As shown by Table IV the outcome of the specifications above are consistent with our previous analysis. We see that aggregate uncertainty explains a non-negligible part of the variation in future excess return. Compared to the regressions made variable by variable, we now find statistical significance on the aggregate loadings across most maturities. Lastly, we do find positive loadings across all maturities, consistent with the notion that agents seek low risk assets if they are faced with ambiguous future economic conditions. This would create an demand effect which would drive future excess returns, hence the positive loadings.

Table IV: Macroeconomic Uncertainty Indices and Bond Risk Premia

	$rx^{(2)}_{t\to t+1}$	$rx^{(3)}_{t\to t+1}$	$rx^{(4)}_{t\to t+1}$	$rx^{(5)}_{t\to t+1}$	$rx^{Avg}_{t\to t+1}$
PCA^{Agg}_t	28.05***	40.55*	55.29*	60.11	46.00*
	(9.79)	(20.73)	(32.30)	(36.98)	(24.86)
c_t	0.01*	0.01**	0.02**	0.02**	0.01**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.12	0.07	0.06	0.05	0.06
#	139	139	139	139	139
PCA^{Good}_t	–22.20	–62.38*	–97.23*	–134.70**	–79.13*
	(19.08)	(35.39)	(49.50)	(63.04)	(41.41)
PCA^{Bad}_t	85.92***	159.10***	231.10***	284.40***	190.10***
	(21.97)	(38.03)	(46.96)	(64.23)	(42.35)
c_t	0.00*	0.01**	0.02**	0.02**	0.01**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.16	0.12	0.12	0.11	0.12
#	139	139	139	139	139
p-Value	0.00	0.00	0.00	0.00	0.00

Note: This table displays the predictive power of our uncertainty indices with respect to future excess returns. The top panel displays the predictive power of our aggregate index and the second panel displays our good and bad uncertainty indices. The sample is quarterly from Q3 1981 to Q4 2016. Newey-West standard errors are in parentheses. The *p-Value* indicates the Wald Test probability under $H_0 : Unc^{Good}_t = Unc^{Bad}_t = 0$. Significance levels: *$p$<10%, **$p$<5%, ***$p$<1%.

In the second panel of Table IV, we show the implications of decomposing uncertainty. We see both good and bad uncertainty coefficients maintaining their signs across all maturities. Consistently with our previous results, we note once again that bad uncertainty is the one with the highest (absolute) impact on bond risk premia. We also observe that loadings on bad uncertainty always exceed the size of aggregate uncertainty. Thus, we confirm the importance of decomposing uncertainty proxies. Moreover, we are able to reduce the standard errors across the two indices simultaneously. Such results strengthen our view that the individual specifications carried too much noise and therefore, decreased statistical significance.

The decomposed specification allows us to provide an economically relevant and statistically significant view of both uncertainty measures simultaneously. Finally, we show how good and bad macroeconomic uncertainty have substantial predictive power on bond risk premia, explaining on average 12 percent of the one year ahead bond excess returns across all maturities, with a peak of 16 percent for the shortest maturity. Thus, we are both able to explain a higher degree of excess return variation as well as refine the predictive power of both predictors for all maturities. This indicates that the construction of uncertainty indices provided real value in terms of refining the shocks to consumption within the model.

We perform the same analysis using the orthogonal uncertainty measures to see how and if the results change due to the inherent correlation between our raw uncertainty measures. Interestingly, in this setting, the uncorrelated uncertainty measures completely maintain their signs and significance. For good uncertainty, we even see the exact same size on the loadings while the size on bad uncertainty loadings is mildly reduced. This is vastly different from the individual regressions where we saw sign switches and inconclusive simultaneous results on the two loadings. This once again strengthens our notion that our individual measures contained a high degree of noise. As we observe small or no changes between regressions using uncorrelated and correlated uncertainty indices, we are confident that the results we document on all index-level tests not are a function of the correlation between the uncertainty indices.

B.3. Uncertainty and Economic Activity

So far, we have observed how decomposing aggregate macroeconomic uncertainty into a good and bad components yields a significant improvement in predictive power with respect to bond risk premia. Moreover, we observed how high good (bad) uncertainty predicts a decrease (increase) in future excess returns and that the size of the loading on bad uncertainty exceeds the size of the loading on aggregate uncertainty. But how does macroeconomic uncertainty relate to the real economy? In other words, do good and bad macroeconomic uncertainty at time t contain valuable information regarding the growth in economic activity between t and $t+1$? These questions are important for two reasons. Firstly, Segal et al. (2014) found evidence that good and bad uncertainties are related to future consumption growth. Secondly, and perhaps more importantly, we have found indications that bad uncertainty is more influential than good uncertainty on future excess returns. We hypothesized that this might be due to a demand effect caused by loss aversion. This raises our need to actually establish a channel from bad uncertainty (in particular) to real economic activity to be able to validate our reasoning.

As discussed in Section IV, past researchers have analyzed the link between macroeconomic uncertainty and bond risk premia and, separately, the link between bond risk premia and the state of the economy. Therefore, we believe there is a gap in exploring the common link among all of the aforementioned elements. After having confirmed and reinforced our expectations about the predictive power of macroeconomic uncertainty with respect to bond risk premia, the next natural step in our analysis is to explore the link between the former and economic activity. To do so, we use one year realized industrial production from Q3 1981 to Q4 2016, as a proxy for economic activity. Note that this is different from Segal et al. (2014) who looks at future consumption growth. We decide to look at industrial production to get a more direct measure of the change in production between t and $t+1$. In essence, we look at how shocks to consumption, or aggregate demand, feed into production, or equivalently, aggregate supply. We are aware of the approximation errors in such test but we believe that these variables are reasonably good proxies for both demand and supply in the aggregate economy. We run two separate regressions where we predict future realized economic activity: (i) using an index of aggregate macroeconomic uncertainty and (ii) using our two indices of good and bad uncertainty.

$$IP_{t\to t+1} = const + \beta PCA_t^{Agg} + error \tag{13}$$

$$IP_{t\to t+1} = const + \beta_g PCA_t^{Good} + \beta_b PCA_t^{Bad} + error \tag{14}$$

Table V reports the results of both regressions. The first important result of our analysis is the sign of the relationship between aggregate uncertainty and realized industrial production. The negative sign is consistent with previous evidence which has documented a negative effect of overall uncertainty on economic activity. However, the loading on aggregate uncertainty is not statistically significant, contrarily to what had been found by Segal et al. (2014). The difference in our result might stem from the difference in approach to measure uncertainty or the fact that we analyze a shorter time-series sample. Nevertheless, the most important finding is presented in the second column of the same table. As in the predictive analysis of individual macroeconomic variables, decomposing uncertainty into good and bad components substantially improves the predictive power of our specification. Not only is the explanatory power of the independent variables increased vastly from close to zero up to 7 percent, but also, both components of uncertainty are now statistically significant. We observe coefficients on the uncertainty indices with signs which are in line with our predictions. We document a significant negative (positive) relationship between bad (good) uncertainty and economic activity, in line with evidence from Segal et al. (2014) and in line with our predictions. Consequently, we are able to confirm the hypothesized link between good and bad macroeconomic uncertainty, bond risk premia and economic activity.

Table V: Predicting Economic Activity

	$IP_{t\to t+1}$	$IP_{t\to t+1}$
$\boldsymbol{PCA_t^{Agg}}$	–26.20	
	(34.29)	
$\boldsymbol{PCA_t^{Good}}$		128.40**
		(56.56)
$\boldsymbol{PCA_t^{Bad}}$		–203.30***
		(56.49)
$\boldsymbol{c_t}$	0.02***	0.03***
	(0.01)	(0.01)
$\boldsymbol{R^2}$	0.01	0.07
#	138	138
***p*-Value**		0.00

Note: This table displays the channel from the uncertainty indices to industrial production growth. We project future growth in industrial production from our uncertainty indices. The sample is quarterly from Q3 1981 to Q4 2016. Newey-West standard errors are in parentheses. The *p-Value* indicates the Wald Test probability under H_0 : $Unc_t^{Good} = Unc_t^{Bad} = 0$. Significance levels: **p*<10%, ***p*<5%, ****p*<1%.

By combining the results from Tables IV and V, we find empirical evidence of the countercyclical component in bond risk premia and we show how decomposed measures of macroeconomic uncertainty such as PCA_t^{Good} and PCA_t^{Bad} yield substantial predictive power in analyzing this component. In essence, we use good and bad macroeconomic uncertainty as a potential link and explanation for the behavior previously presented in Figure 1. That is, we find that an increase in bad (good) macroeconomic uncertainty in t predicts both higher (lower) bond risk premia and lower (higher) economic activity in $t+1$. These results are not straightforward to interpret. However, in our predictions, we emphasized the notion of economic agents seeking assets which exhibit a negative comovement with economic activity aiming to smooth their utility. What we find here is exactly that. For example, bad uncertainty in t predicts a contraction in the economy between t and $t+1$ at the same time as excess returns are predicted to increase over the same period. This implies that bonds have high payoffs in those times economic activity is low, which is exactly what the countercyclical component indicates. What we have done is to link this feature to good and bad uncertainty, something we have not found in previous research. It is non-trivial to assess what makes bonds exhibiting this feature, but one explanation could be the flight-to-quality trait. That is, in the wake of bad economic conditions, funds are pulled from high risk assets such as stocks, which often have positive comovement with economic activity, and put into low risk assets such as U.S. government securities. This causes a demand effect in bonds which makes prices increase and therefore, increases the excess returns available to investors at $t+1$. In other words, the empirical results are so far both in line with the economic model on which they are built and with our empirical predictions.

B.4. Controlling for Financial Factors

In this section we seek to explore whether the proposed measures of macroeconomic uncertainty incorporate information regarding bond risk premia that cannot be explained by simply using financial factors related to the yield curve. This is important as we need to shed light on the actual relevance of our uncertainty measures and make sure that they are not a repackaging of already existing risk factors. In particular, we control for the five forwards factors developed by Cochrane and Piazzesi (2005), found to explain almost 40 percent of the variation in future excess returns. Previous research such as Ludvigson and Ng (2009) has already documented that macroeconomic risks adds predictive power over and above models based on financial factors. Thus, it is of great interest to investigate whether our factors of macroeconomic uncertainty exhibits the same pattern in order to be able to confirm the strength of our previous findings.

As a first step, we build Cochrane and Piazzesi (2005) forward factors and run the same regression as the one in the original paper. The upper panel of Table X reports the results of such regression. We find slightly smaller R^2 and we cannot validate the tent-shaped structure of the loadings. However, we believe such differences can be attributed to the shorter time horizon and the different sampling frequency used in our analysis. Following this, we add the two indices of good and bad macroeconomic uncertainty to the regression. The results of our analysis are reported in the lower panel of Table X. For the sake of brevity we do not report coefficients and standard errors of the five forward factors as this not is the core of the analysis. We find empirical evidence that our uncertainty measures in fact do contain information with respect to bond risk premia that is not already included in financial factors. Both measures of uncertainty keep being statistically significant for most maturities when controlling for Cochrane and Piazzesi (2005) forward factors. Moreover, we observe an increase in the overall explanatory power ranging from around 3 up to 5 percent for all maturities. Note that while we only report simple R^2 in our analysis, we have confirmed the results using adjusted measures, accounting for the increased number of independent variables. We find that the improvement in the explanatory value, measured by the adjusted R^2, is close to those shown using the unadjusted measure. Thus, we are confident that our measures contain new information regarding bond risk premia not contained in the yield curve. Additionally, it is interesting to note that adding the two macroeconomic factors seems to have more pronounced effect on the predictive power for longer maturities. This is an interesting feature which opens up to a completely new field of analysis. As this topic lies somewhat outside the scope of our paper, we will not dwell on the potential explanations for this phenomenon for too long. However, we do know that longer maturity bonds are more risky for several reasons. What we see in our results is that good and bad uncertainty factors are able to provide more new information over and above financial risks for these long-term bonds, which would indicate that at least some parts of the risks in these bonds are more about economic risks rather than financial risks. Building on evidence from Campbell and Viceira (2001), one explanation is that long-term bonds are held by investors that use the bonds as a hedging instrument to smooth consumption. This argument suits our predictions quite well and the results might indicate that our good and bad uncertainties do a good job in capturing this hedging feature, something that potentially is overlooked by financial factors.

It is important to observe that our empirical findings further strengthen claims made in previous literature. That is, not only are macroeconomic factors strongly associated with part of the predictable variation in bond risk premia, but they also contain information that is substantially different from common financial factors such as the Cochrane and Piazzesi (2005) forward factors. We are therefore contributing to research documenting violations of the Expectation Hypothesis, which states that all information regarding bond returns and yields is contained in factors derived from the term structure of interest rates. Furthermore, we demonstrate that models based on yield curve factors are missing an economically relevant part of the information useful to understand the time-variation in excess bond returns, increasingly so for longer maturity bonds.

B.5. Controlling for Macroeconomic Factors

For an in-depth test and further validation of our analysis, it is of interest to control whether our measures of macroeconomic uncertainty keep being significant when controlling for macroeconomic risk factors proposed and tested by previous literature. This is important as we need to make sure that our proxies are unique and not overlapping with factors already documented by previous research. Specifically, we believe the aggregate uncertainty measure derived in Ludvigson et al. (2015) to be particularly relevant. Ludvigson et al. (2015) use a PCA to extract a broad measure of uncertainty from a set of 132 macroeconomic time series which they explicitly define as *a benchmark to evaluate theories for which uncertainty shocks play a role in business cycles*. Moreover, this serves as a particularly strong test as they indicate that measures based on cross sectional dispersion, such as the ones used in this paper, might be an inferior proxy for uncertainty. For the sake of brevity, we will refer to such measure as *LN* in the following paragraphs.

We run three predictive regressions of future excess returns. Firstly, we use the *LN* factor stand alone, aiming to prove that the it does exhibit predictive abilities with respect to future excess returns. We expect it to have the same sign as our aggregate index as they aim to capture similar information. Secondly, we use the aggregate uncertainty index in combination with the *LN* factor. This regression is performed to observe whether our index of aggregate macroeconomic uncertainty has stronger explanatory power than the *LN* factor or if it add additional information with respect to changes in bond risk premia. As the *LN* measure is much broader, we would expect it to be superior to ours. Lastly, we use our good and bad uncertainty indices in combination with the *LN* factor. The goal is to once again test whether disentangling the good and the bad components of uncertainty adds value and enhances the predictive power. Based on our previous analysis, we expect the decomposition to deliver substantial improvements in significance and explanatory power when compared to the aggregate index. However, as the *LN* factor is much broader and built on a more sophisticated econometric framework, we cannot be certain that our good and bad uncertainty indices will maintain their predictive abilities.

The results are reported in Table XI. The top panel documents that the *LN* measure does contain predictive power with respect to future excess return, with high explanatory value. The overall performance of the *LN* measures is stronger than our aggregate index on a stand alone basis, but the sign of the loadings is positive confirming our expectations. In the second panel, we find evidence that PCA^{Agg} explains part of variation in bond risk premia that previously was attributed to the *LN* factor. This can be seen by the smaller slope coefficients of the *LN* factor and its decreased significance. However, we do not find statistically significant results for the loadings on PCA^{Agg}, something previously found on a stand alone basis in Table IV. This indicates that our aggregate uncertainty measure is inferior to the broader metric which we control for, but that it does capture some of the information previously associated with the *LN* measure. In the third panel of Table XI, the results are surprising: PCA^{Good} and PCA^{Bad} appear to act as confounding variables in the regression. That is, the two uncertainty indices seem to explain most of the correlation between the *LN* measure and bond risk premia. While the slope coefficients of the *LN* factor drop drastically and its statistical significance is lost if compared to the first and second panels, the loadings on our good and bad uncertainty indices show little to no change compared to the predictive analysis in Section V.A. Accordingly, we can confirm that decomposing uncertainty does indeed provide additional value. These results are even more striking when considering that our two indices are constructed by using only three macroeconomic time series, while the *LN* factor is derived through a factor analysis of more than 130 variables. The reported results might be an indication that RGDP, RCONS and CPI, in general, are some of the key drivers in overall macroeconomic uncertainty and that good and bad uncertainty factors, in particular, drive the understanding of future excess returns. If that is the case, other categories of macroeconomic variables included in the *LN* factor such as employment, housing starts and inventories do not provide additional information and might instead be causally related to the main factors analyzed in this paper, which seem to explain most of their variability.

C. *Cross Sectional Implications for Bond Risk Premia*

One of the central findings in Segal et al. (2014) is the evidence that good uncertainty carries a positive market price of risk, while bad uncertainty has a negative price of risk. This indicates that the high risk states for investors are those with high bad and low good uncertainty. Accordingly, due to the difference in econometric approach, it is of value to investigate if we can confirm such finding. To do so, we follow Segal et al. (2014) and use the Fama and MacBeth (1973) procedure. We start by running a time series regression according to:

$$rx^{(n)}_{t\to t+1} = const + \beta^{(n)}_g PCA^{Good}_{t+1} + \beta^{(n)}_b PCA^{Bad}_{t+1} + error \tag{15}$$

The main difference in this specification compared to the ones used so far is the time-indexing. Note that this regression investigates the contemporaneous effects of our good and bad uncertainty indices on excess returns. That is, each uncertainty measure now captures the uncertainty in $t+1$ about realization in $t+2$, while the excess bond returns is measured as the realized excess returns in $t+1$. The betas from this regression are used in the second step to estimate the slope in the cross section, or equivalently, the prices of the risk factors:

$$\overline{rx}^{(n)} = \tilde{\lambda}_g \beta^{(n)}_g + \tilde{\lambda}_b \beta^{(n)}_b \tag{16}$$

Like Segal et al. (2014), we run the second step without intercept. The estimated factor risk premia $\tilde{\Lambda} = (\tilde{\lambda}_g, \tilde{\lambda}_b)$ can be viewed as containing both the price of risk and the quantity of risk. Accordingly, we multiply with the inverse of the quantity of risk (the unconditional variance-covariance matrix) to obtain the price of risk, denoted λ_i for $i = \{Good, Bad\}$. As it can be seen in the top panel of Table XII in Appendix A, the market price of good uncertainty is positive and the price of bad uncertainty is negative. Thus, we are able to confirm the central finding from Segal et al. (2014). We have previously presented evidence that high bad uncertainty in t is bad for future economic activity in $t+1$ as measured by the growth in industrial production. Subsequently, we see high bad uncertainty being a high risk state for investors. Similarly, we know that good uncertainty predicts increases in future economic activity, therefore being a low risk state.

In isolation, these numbers might be hard to understand. Accordingly, we need to put them into an economic context. To build further intuition on this, we consider two assets, where the first asset loads heavily on good uncertainty and the second asset loads heavily on bad uncertainty. All else equal, an investor would require higher compensation for the first asset compared to the second asset. Intuitively, the first asset would show high returns in states of the world where there are high good shocks to consumption. This positive comovement decreases the diversification between consumption growth and financial wealth. Consequently, the investor demands a higher average excess return for this risk. Similarly, the second asset serves as an insurance against bad economic times. The intuition behind this is that when there is high bad shocks to consumption in $t+1$ that depress consumption, the price of the asset increases. Thus, this insurance feature lowers the average excess return, indicating that the investor is willing to pay a premium for the second asset. Based on this reasoning, we see that standard economic intuition is in line with our empirical results.

We quantify the implications of our findings in the second panel of Table XII in Appendix A. Firstly, the uncertainty loadings from the first pass regression are positive for all maturities and for both uncertainty measures. This contradicts the results from Segal et al. (2014) and it is different from our findings from the predictive regressions. Nevertheless, average excess returns are defined as:

$$\overline{rx} = \Lambda' \Omega \beta \tag{17}$$

where Λ is the market prices of risk for the risk factors, Ω is the variance-covariance matrix and β is loadings from the first pass regressions. Note that we have dropped the maturity superscript. We see that the good uncertainty contribute positively to the excess returns, while the bad uncertainty decrease the excess returns. This indicates that in the wake of high good uncertainty, prices are on average low and therefore contributing to a positive risk premia. Similarly, once in a state with high bad uncertainty, prices are on average high, contributing to a decreased risk premia on average. This is in line with our previous discussion regarding the comovement of consumption shocks. Since the risk factors are correlated, there is an interaction term involving the off-diagonal elements in the matrix of the unconditional variance-covariance. Estimating the the model parameters and the implied average excess returns, we see that the model gives an average excess return for all maturities that is very close to what is observed in the data.

Though there might be several potential explanations for this, we find evidence in favor of the argument that economic agents seek low-risk assets in the presence of high bad economic uncertainty. This is in line with the discussion we outlined before regarding the flight-to-quality in U.S. government securities. Thus, the negative price of risk combined with positive loading in the first step regression is consistent with the notion that agents dislike bad uncertainty causing prices to increase between time t and $t+1$ due to a potential demand effect and therefore creating high excess returns in bad states of the world. Something that we presented evidence for in Section V.B.3. In other words, we can confirm our previous empirical results.

VI. Out-of-Sample Analysis

To make sure that our result of risk premia predictability is not a function of fitting the data, we perform statistical sanity checks, or robustness tests, by using an out-of-sample forecast. We initiate our analysis by following Eriksen (2015) in his method of assessing the out-of-sample performance. This is done according to:

$$R^2_{oos} = 1 - \frac{\sum_{j=1}^{N}\left(rx^{(n)}_{t+1} - \widehat{rx^{(n)}_{t+1,i}}\right)^2}{\sum_{j=1}^{N}\left(rx^{(n)}_{t+1} - \widehat{rx^{(n)}_{t+1,c}}\right)^2} \tag{18}$$

where $\widehat{rx^{(n)}_{t+1,i}}$ is the predicted excess return from our model for maturity n in each quarter of the forecasting window which goes from j to N. We label $\widehat{rx^{(n)}_{t+1,c}}$ as the projected excess return in a benchmark model. To account for the fact that the prediction should only incorporate information known in t, we estimate the index weights for the good and bad uncertainty index in an expanding setting. That is, we re-estimate both index weights from the PCA quarter by quarter. This implies that the information on which each index weight is estimated is purely backwards looking in t. Arguably, this is as close as one can come to a real-time update of beliefs and since there is no direct risk of revision in the SPF data, we can be quite sure that no forward looking bias is incorporated in the two uncertainty indices. However, after inspecting the evolution of the index weights over time, it is evident that they are surprisingly stable and the results are basically the same even if we allow for fixed index weights. The initial estimation window covers 1981 Q3 to 1996 Q3, after which we include one quarter of data as we move forward in time. This implies that the initial forecast window is 1996 Q4 to 2016 Q4. Thus, at each point of forecasting, we have index weights which are purely backward looking in t which are used to project excess returns in $t + 1$. We perform two such out-of-sample test. Firstly, we put our good and bad uncertainty indices as model $i = PCA$ against a benchmark model, $c = EH$, consisting of a constant that effectively characterize a model similar to the Expectation Hypothesis. As Ludvigson and Ng (2009), we perform a second test in which we incorporate the forward factors of Cochrane and Piazzesi (2005), denoted CP, in both i and in c. If we do find that our mean squared prediction errors is smaller than those of the new benchmark model, we can affirm that a model of good and bad uncertainty provides value over and above the information contained in the yield curve, even out-of-sample. In both specifications, we follow the expanding window estimation for both index weights and any forward factors. To assess any statistical significance of our out-of-sample R^2_{oos}, we use the method proposed by Clark and West (2007). In this setting, we try to estimate a bias adjusted difference in the mean squared prediction errors between model i and model c. The initial bias stems from the fact that the forecast variables between the models differ.

$$\Psi_{t+1} = \left(rx_{t+1}^{(n)} - \widehat{rx_{t+1,c}^{(n)}}\right)^2 - \left[\left(rx_{t+1}^{(n)} - \widehat{rx_{t+1,i}^{(n)}}\right)^2 - \left(rx_{t+1,c}^{(n)} - \widehat{rx_{t+1,i}^{(n)}}\right)^2\right] \tag{19}$$

We project Ψ_{t+1} from a constant. We once again use a Newey and West (1987) correction over the last year to correct for the autocorrelation in the error terms. We derive the p-values from this regression to assess the statistical significance of our out-of-sample performance. Our out-of-sample performance is presented in Table VI.

Table VI: Out-of-Sample Performance

Model Specification	$\boldsymbol{rx^{(2)}}$	$\boldsymbol{rx^{(3)}}$	$\boldsymbol{rx^{(4)}}$	$\boldsymbol{rx^{(5)}}$	$\boldsymbol{\overline{rx}}$
$i = PCA$, $c = EH$	0.14	0.10	0.09	0.07	0.09
	[0.01]	[0.02]	[0.03]	[0.04]	[0.03]
$i = PCA + CP$, $c = EH + CP$	0.04	0.05	0.04	0.02	0.04
	[0.11]	[0.09]	[0.14]	[0.21]	[0.15]

Note: This table displays the R^2_{oos} for all maturities across two specifications. The first specification test our uncertainty indices, denoted *PCA* (note that this notation includes both good and bad uncertainty indices), against a benchmark of the Expectation Hypothesis, denoted *EH*. The second specification includes the forward factors from Cochrane and Piazzesi (2005), denoted *CP*, in both the benchmark and the uncertainty estimation. The initial forecast window covers 1996Q4 to 2016Q4. We present the adjusted p-value, estimated using the method proposed by Clark and West (2007), in brackets.

If values in Equation 17 comes out positive, the denominator is effectively larger than the numerator, indicating that the squared prediction errors in specification i is lower than in c. This would indicate that our model performs well out-of-sample compared to the benchmark model. In the first specification, the values goes from 14 percent for the two year bond and decreases monotonically to 7 percent for the five year bond. On average, we do see that the mean squared prediction errors from our model i indeed are lower than those of the benchmark model c, indicating that the empirical results holds out-of-sample. Adding to this, we present p-values in brackets that are below 5 percent for all maturities, indicating a solid out-of-sample performance from a statistical perspective. In the second specification, we find a reduction in the R^2_{oos}, but still positive values through out all maturities. First of all, we want to raise a word of caution regarding the results from the second specification as the structure of our forward factors not are as the one in the original paper. Nevertheless, for the two year bond we find a value of 5 percent and for the five year bond, the corresponding value is 2 percent. However, the p-values increase and we only find significant support for an out-of-sample performance for the 3 year bond. Otherwise, the statistical significance is low. Despite these issues in the second specification, we do find support that our empirical specification of good and bad uncertainty perform well out-of-sample and that there are some, but weak, indications that we maintain incremental explanatory power out-of-sample even when controlling for information contained in the yield curve.

VII. Concluding Remarks

In this paper, we present a new characterization of the previously documented countercyclical trait in bond risk premia and we reinforce the importance of macroeconomic risks in understanding excess bond returns. We do so by using survey data of individual forecasts for Real GDP, Inflation and Real Personal Consumption. We construct uncertainty measures based on the semi-variances from each forecast distribution, which are used to create indices for aggregate, good and bad macroeconomic uncertainty. We build our analysis on a model in which these uncertainties drive shocks to future consumption. In the data, we document that good and bad uncertainty have polarized effects on future excess returns. More specifically, we find evidence that good (bad) macroeconomic uncertainty predicts decreased (increased) future excess returns and that these factors explain up to 16 percent of the total variation in future excess returns. This finding is robust after controlling for both financial factors and broader measure of macroeconomic uncertainty. We are therefore presenting evidence that good and bad uncertainty add information over and above what is implied by the yield curve. Also, we provide evidence that our decomposed uncertainty indices contain more information compared to an aggregate uncertainty factor based on more than 130 macroeconomic variables.

Furthermore, we confirm the finding that good and bad uncertainty are related to future economic activity. We find that good (bad) uncertainty predicts an increase (decrease) in future industrial production growth. This, in combination with the fact that good (bad) uncertainty contributes positively (negatively) to risk premia, indicates that bonds have high payoffs in bad states of the world and that agents are paying a premium for this insurance feature. This is to the best of our knowledge a new potential explanation for the countercyclical component in bond risk premia. Our results are stable even out-of-sample and when controlling for the correlation structure between our uncertainty measures. We are therefore confident that our results are not a product of either fitting the data or collinearity.

Despite the fact that our empirical analysis rests upon previous theoretical work, we do find some limitations and issues in our approach that could be good starting points for future research. A main issue in our paper is related to the construction of our uncertainty measures. Although the time-variation of our proxies is closely related to those of other researchers, we believe that a more robust econometric framework has to be developed in separating uncertainties as we consistently find evidence that the decomposition adds predictive power. Consequently, we individuate the need of finding a general method of uncertainty construction. Related to this, our findings indicate that a deeper theoretical investigation of the initiation of uncertainty is crucial as it would increase the understanding of the causality between supply and demand shocks. On a different but equally important note, we document incremental explanatory value of our uncertainty measures for longer maturity bonds when controlling for financial risk factors. This is also a puzzling feature which deserves deeper analysis.

Nevertheless, in order to properly understand bond risk premia, our empirical work shows the importance of separating uncertainty into good and bad components. Furthermore, this separation also provides a economically relevant explanation for the previously documented countercyclical component in bond risk premia.

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APPENDIX A. Tables

Table VII: Uncertainty About Real GDP Growth and Bond Risk Premia

	$rx^{(2)}_{t\to t+1}$	$rx^{(3)}_{t\to t+1}$	$rx^{(4)}_{t\to t+1}$	$rx^{(5)}_{t\to t+1}$	$rx^{Avg}_{t\to t+1}$
Unc^{Agg}_t	–3.48	–14.80	–23.93	–33.40	–18.90
	(8.68)	(15.90)	(21.97)	(26.66)	(18.23)
c_t	0.01***	0.02***	0.02***	0.03***	0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.00	0.01	0.02	0.02	0.02
#	166	166	166	166	166
Unc^{Good}_t	–73.19**	–151.90***	–219.70***	–282.70***	–181.90***
	(30.65)	(55.79)	(78.06)	(93.73)	(64.09)
Unc^{Bad}_t	16.58**	24.64*	32.39	38.32	27.98
	(8.39)	(14.84)	(20.72)	(24.94)	(17.12)
c_t	0.01***	0.02***	0.03***	0.03***	0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.05	0.07	0.08	0.08	0.07
#	166	166	166	166	166
***p*-Value**	0.04	0.03	0.02	0.01	0.02

Note: This table shows the regression of uncertainty about the Real GDP growth and the bond risk premia. The independent variables are both the aggregate uncertainty and good and bad uncertainty about the Real GDP growth. Dependent variables are excess bond returns with a holding period of one year. Numbers in superscript equals the maturity $n - years$. The *p-Value* indicates the Wald Test probability under $H_0 : Unc^{Good}_t = Unc^{Bad}_t = 0$. The sample is quarterly 1974Q4 to 2016Q4. Newey-West standard errors are in parentheses. Significance levels: *p<10%, **p<5%, ***p<1%.

Table VIII: Uncertainty About Inflation and Bond Risk Premia

	$rx^{(2)}_{t\to t+1}$	$rx^{(3)}_{t\to t+1}$	$rx^{(4)}_{t\to t+1}$	$rx^{(5)}_{t\to t+1}$	$rx^{Avg}_{t\to t+1}$
Unc^{Agg}_t	30.44**	43.92	61.56	64.33	50.06
	(13.66)	(27.57)	(43.32)	(49.69)	(33.52)
c_t	0.01***	0.01***	0.02***	0.03***	0.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.09	0.05	0.05	0.04	0.05
#	139	139	139	139	139
Unc^{Good}_t	–4.53	–25.31	–48.44	–74.22	–38.12
	(15.46)	(28.82)	(41.23)	(50.28)	(33.70)
Unc^{Bad}_t	133.00***	247.00***	384.20***	470.70***	308.70***
	(38.07)	(69.34)	(89.75)	(119.80)	(78.30)
c_t	0.00**	0.01**	0.01**	0.02**	0.01**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.14	0.11	0.12	0.11	0.12
#	139	139	139	139	139
p-Value	0.00	0.00	0.00	0.00	0.00

Note: This table shows the regression of uncertainty about the Inflation rate and the bond risk premia. The independent variables are both the aggregate uncertainty and good and bad uncertainty about the Inflation. Dependent variables are excess bond returns with a holding period of one year. Numbers in superscript equals the maturity $n-years$. The *p-Value* indicates the Wald Test probability under $H_0 : Unc^{Good}_t = Unc^{Bad}_t = 0$. The sample is quarterly 1981Q3 to 2016Q4. Newey-West standard errors are in parentheses. Significance levels: *p<10%, **p<5%, ***p<1%.

Table IX: Uncertainty About Real Consumption and Bond Risk Premia

	$rx^{(2)}_{t\to t+1}$	$rx^{(3)}_{t\to t+1}$	$rx^{(4)}_{t\to t+1}$	$rx^{(5)}_{t\to t+1}$	$rx^{Avg}_{t\to t+1}$
Unc^{Agg}_t	27.57	36.19	45.87	51.65	40.32
	(21.17)	(39.55)	(58.21)	(66.08)	(45.99)
c_t	0.01**	0.01***	0.02***	0.03***	0.02***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.05	0.02	0.02	0.01	0.02
#	139	139	139	139	139
Unc^{Good}_t	–28.67	–73.91	–101.60	–123.20	–81.85
	(24.66)	(55.50)	(82.78)	(104.30)	(66.51)
Unc^{Bad}_t	114.80**	270.00**	274.60**	322.90**	229.80**
	(50.17)	(92.06)	(130.60)	(150.50)	(105.40)
c_t	0.01**	0.01**	0.02***	0.02***	0.01***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.10	0.08	0.07	0.07	0.08
#	139	139	139	139	139
p-Value	0.07	0.08	0.11	0.10	0.09

Note: This table shows the regression of uncertainty about the Real Personal Consumption Expenditure growth and the bond risk premia. The independent variables are both the aggregate uncertainty and good and bad uncertainty about the Real Personal Consumption growth. Dependent variables are excess bond returns with a holding period of one year. Numbers in superscript equals the maturity $n-years$. The *p-Value* indicates the Wald Test probability under $H_0 : Unc^{Good}_t = Unc^{Bad}_t = 0$. The sample is quarterly 1981Q3 to 2016Q4. Newey-West standard errors are in parentheses. Significance levels: *p<10%, **p<5%, ***p<1%.

Table X: Controlling for Financial Factors

	$rx^{(2)}_{t\rightarrow t+1}$	$rx^{(3)}_{t\rightarrow t+1}$	$rx^{(4)}_{t\rightarrow t+1}$	$rx^{(5)}_{t\rightarrow t+1}$	$rx^{Avg}_{t\rightarrow t+1}$
f_t^1	0.15	0.22	0.14	0.11	0.15
	(0.45)	(0.87)	(1.21)	(1.53)	(1.01)
f_t^2	–1.47**	–3.22**	–4.43**	–5.13**	–3.56**
	(0.74)	(1.36)	(1.90)	(2.37)	(1.57)
f_t^3	1.88***	4.23***	5.40***	5.93***	4.36***
	(0.58)	(1.11)	(1.63)	(2.13)	(1.34)
f_t^4	0.26	0.38	1.28	1.36	0.82
	(0.28)	(0.57)	(0.84)	(1.10)	(0.69)
f_t^5	–0.59**	–1.26***	–1.93***	–1.69*	–1.37**
	(0.23)	(0.48)	(0.71)	(0.94)	(0.59)
c_t	–0.01	–0.01	–0.01	–0.02	–0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
R^2	0.34	0.29	0.29	0.24	0.28
#	139	139	139	139	139
PCA_t^{Good}	–33.60	–78.53	–122.90*	–172.00**	–101.80*
	(25.69)	(47.74)	(64.53)	(82.65)	(54.98)
PCA_t^{Bad}	47.58*	93.04*	142.30**	198.10**	120.20**
	(26.99)	(49.33)	(66.75)	(84.79)	(56.67)
c_t	–0.01	–0.01	–0.02	–0.03	–0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
R^2	0.36	0.32	0.33	0.29	0.31
#	139	139	139	139	139
p-Value	0.21	0.17	0.10	0.06	0.11

Note: This table displays the impact of the macroeconomic uncertainty over and above the factors developed by Cochrane and Piazzesi (2005). The top panel displays the forward factors and the second panel the same regression but including the PCA-index for good and bad uncertainty. In the second panel, we do not display the loadings from the first panel. The sample is quarterly from Q3 1981 to Q4 2016. Newey-West standard errors are in parentheses. The *p-Value* indicates the Wald Test probability under H_0 : $Unc_t^{Good} = Unc_t^{Bad} = 0$. Significance levels: *$p$<10%, **$p$<5%, ***$p$<1%.

Table XI: Controlling for Macroeconomic Factor

	$rx^{(2)}_{t\to t+1}$	$rx^{(3)}_{t\to t+1}$	$rx^{(4)}_{t\to t+1}$	$rx^{(5)}_{t\to t+1}$	$rx^{Avg}_{t\to t+1}$
LN_t	0.10**	0.16**	0.20**	0.23**	0.17**
	(0.04)	(0.06)	(0.09)	(0.11)	(0.07)
c_t	–0.08**	–0.13**	–0.16*	–0.18*	–0.14*
	(0.03)	(0.06)	(0.08)	(0.10)	(0.07)
R^2	0.13	0.10	0.08	0.07	0.08
#	139	139	139	139	139
LN_t	0.07*	0.13*	0.15	0.17	0.13
	(0.04)	(0.07)	(0.10)	(0.13)	(0.08)
PCA^{Agg}_t	15.41	15.49	26.66	26.11	20.92
	(12.22)	(26.06)	(41.09)	(46.89)	(31.39)
c_t	–0.05	–0.11	–0.12	–0.14	–0.10
	(0.04)	(0.07)	(0.10)	(0.12)	(0.08)
R^2	0.15	0.11	0.09	0.07	0.09
#	139	139	139	139	139
LN_t	0.05	0.10	0.11	0.13	0.10
	(0.04)	(0.07)	(0.09)	(0.11)	(0.07)
PCA^{Good}_t	–25.30	–68.46*	–103.60**	–142.00**	–84.85**
	(19.17)	(34.97)	(49.08)	(63.42)	(41.30)
PCA^{Bad}_t	67.39***	122.90***	193.10***	240.80***	156.00***
	(23.68)	(41.04)	(54.95)	(67.54)	(46.16)
c_t	–0.04	–0.08	–0.08	–0.10	–0.08
	(0.03)	(0.06)	(0.08)	(0.10)	(0.07)
R^2	0.18	0.14	0.13	0.12	0.13
#	139	139	139	139	139
p-Value	0.02	0.01	0.00	0.00	0.00

Note: This table displays the uncertainty measure developed by Ludvigson et al. (2015) and our PCA-index of good and bad uncertainty as well as aggregate uncertainty. The top panel displays the predictive power of the uncertainty measure developed by Ludvigson et al. (2015). The second panel performs the same regression but control our index of aggregate uncertainty. The last panel control for our PCA-indices of good and bad uncertainty. The sample is quarterly from Q3 1981 to Q4 2016. Newey-West standard errors are in parentheses. The *p-Value* indicates the Wald Test probability under $H_0 : Unc^{Good}_t = Unc^{Bad}_t = 0$. Significance levels: *$p$<10%, **$p$<5%, ***$p$<1%.

Table XII: Price of Risk and Risk Premia Implications

	PCA^{Good}	PCA^{Bad}
λ	569.53***	–497.00*
	(14.82)	(148.36)

Risk Premia Decomposition

	Data	*Model*	PCA^{Good}	PCA^{Bad}	PCA^{Good}, PCA^{Bad}
$rx^{(2)}$	1.00	1.02	2.32	–2.48	1.18
$rx^{(3)}$	1.86	1.98	4.81	–3.09	0.25
$rx^{(4)}$	2.63	2.53	6.14	–4.09	0.48
$rx^{(5)}$	3.10	3.10	7.61	–4.51	0.00

Note: The first panel of this table displays the prices of risk for the good and bad uncertainty, lambdas are divided by 100. The second panel decomposes the average excess return into the contributing parts, where the column "Model" summarize the Good uncertainty (PCA^{Good}), Bad uncertainty (PCA^{Bad}) and Covariance term (PCA^{Good}, PCA^{Bad}). These numbers are given in percent. The sample is quarterly from Q3 1981 to Q4 2016. Newey-West standard errors are in parentheses. Significance levels: *p<10%, **p<5%, ***p<1%.

Table XIII: Yearly Overview of Macroeconomic Indicators

	Real GDP Growth					Real Consumption Growth					Inflation				
Year	***Mean***	***Max***	***Min***	***Std.***	***#***	***Mean***	***Max***	***Min***	***Std.***	***#***	***Mean***	***Max***	***Min***	***Std.***	***#***
1974	0.70	3.61	−4.64	1.57	48										
1975	4.62	9.70	−8.50	3.24	162										
1976	6.22	9.16	0.94	1.32	156										
1977	5.61	8.67	−3.06	1.54	144										
1978	3.52	7.06	−3.69	2.02	108										
1979	0.23	4.63	−4.93	1.65	120										
1980	0.86	5.84	−5.66	2.35	97										
1981	2.69	6.23	−4.03	1.63	126	3.47	9.50	−1.04	1.77	51	7.90	12.50	1.13	1.96	67
1982	3.24	5.92	−2.68	1.31	132	3.58	8.89	−0.52	1.39	105	5.97	8.70	0.40	1.27	124
1983	5.37	7.83	1.11	1.00	117	4.56	12.39	2.06	1.09	102	4.65	6.60	−1.01	1.39	118
1984	4.32	7.44	1.63	1.03	102	4.11	6.56	1.77	0.82	82	5.06	7.60	0.60	1.22	103
1985	3.80	5.65	0.94	0.91	91	3.42	6.30	1.07	1.10	75	4.50	6.30	2.50	0.79	90
1986	3.62	5.35	0.58	0.91	84	3.11	7.88	−0.39	1.36	72	3.84	5.50	0.80	0.71	86
1987	3.18	4.80	0.23	0.86	75	2.64	4.21	−0.12	0.96	66	4.31	6.10	1.50	0.74	78
1988	2.87	4.27	−0.52	0.86	55	2.38	4.18	−1.01	0.96	51	4.85	6.20	3.80	0.56	59
1989	2.39	4.59	0.22	0.88	53	2.32	4.82	1.00	0.81	44	4.67	6.50	3.09	0.72	51
1990	1.41	3.59	−0.67	1.19	57	1.59	4.05	−0.85	1.20	54	4.31	6.20	2.72	0.71	57
1991	2.67	4.78	0.41	0.93	130	2.42	4.05	−0.03	0.83	128	3.81	5.09	2.70	0.47	131
1992	3.39	5.33	2.13	0.62	136	2.99	4.93	1.97	0.55	134	3.54	4.90	2.50	0.49	132
1993	3.65	5.90	1.32	0.55	121	3.47	6.45	1.02	0.67	120	3.38	5.23	2.30	0.51	119
1994	3.44	5.53	2.28	0.50	113	3.27	4.63	2.33	0.40	110	3.38	4.50	2.40	0.44	109
1995	3.06	5.00	1.78	0.49	163	2.86	4.13	1.51	0.49	158	3.36	5.20	2.50	0.48	159
1996	2.71	3.83	1.37	0.50	140	2.67	4.10	1.21	0.55	137	3.04	4.60	2.09	0.44	144
1997	2.90	4.25	2.00	0.47	139	3.05	4.36	1.91	0.54	136	2.98	4.09	2.10	0.43	136
1998	2.86	4.69	1.55	0.62	111	3.50	5.90	1.84	0.66	111	2.47	3.20	1.20	0.40	110
1999	3.41	5.05	1.52	0.68	140	3.52	5.35	2.20	0.69	130	2.40	3.50	1.40	0.42	134
2000	3.95	5.86	2.41	0.61	120	3.82	5.86	2.31	0.63	115	2.60	4.40	1.50	0.47	113
2001	2.93	4.39	0.44	0.84	120	2.93	4.25	−0.07	0.86	117	2.51	3.30	1.10	0.43	116
2002	3.71	5.09	1.24	0.64	127	3.20	4.45	0.07	0.74	125	2.38	3.50	1.09	0.40	126
2003	4.27	6.09	1.27	0.80	126	3.84	5.27	1.49	0.68	126	2.15	3.09	1.76	0.43	123
2004	4.65	6.22	3.60	0.54	116	4.10	5.38	2.62	0.53	115	2.21	4.50	1.09	0.61	112
2005	4.17	5.86	2.65	0.49	175	3.78	5.32	2.27	0.55	173	2.40	4.80	0.45	0.54	173
2006	3.63	5.17	1.76	0.58	191	3.49	5.10	1.70	0.57	183	2.39	4.53	−0.09	0.62	186
2007	3.25	4.34	1.80	0.49	180	3.10	4.18	1.17	0.55	177	2.34	3.30	0.21	0.55	176
2008	1.59	3.88	−1.87	1.26	175	1.49	3.66	−2.46	1.17	171	2.41	4.60	0.56	0.70	171
2009	1.80	5.46	−3.43	1.78	156	1.62	4.11	−2.05	1.14	153	1.95	5.11	−0.50	0.87	148
2010	3.53	5.76	2.06	0.67	152	3.03	4.78	1.62	0.63	150	1.93	3.40	−0.26	0.70	150
2011	3.57	5.48	1.57	0.76	156	3.17	4.54	1.92	0.61	155	2.10	4.39	−0.99	0.76	152
2012	2.92	4.17	0.69	0.56	153	2.80	4.13	1.53	0.48	148	2.19	3.40	−0.27	0.59	148
2013	3.18	4.25	2.00	0.48	154	2.95	4.21	1.83	0.51	145	2.10	3.01	−0.15	0.45	148
2014	3.60	5.26	2.22	0.55	152	3.38	5.04	2.01	0.60	143	2.01	3.10	0.67	0.43	153
2015	3.42	4.48	2.12	0.44	152	3.57	4.73	2.14	0.52	143	2.12	3.30	0.74	0.46	151
2016	2.87	4.03	1.83	0.37	147	3.04	4.14	1.62	0.36	139	2.17	3.40	0.66	0.43	149
Total	3.35	9.70	−8.50	1.59	5472	3.12	12.39	−2.46	1.01	4344	2.99	12.50	−0.99	1.35	4502

Note: Overview of the macroeconomic indicators used in this paper. All numbers are in percent except # (number observations) and grouped by year. Due to data availability, Real Consumption Growth and Inflation starts in Q3 1981. Real GDP Growth starts in Q4 1974. All indicators ends in Q4 2016.

APPENDIX B. Figures

Figure 2: Good and Bad Uncertainties

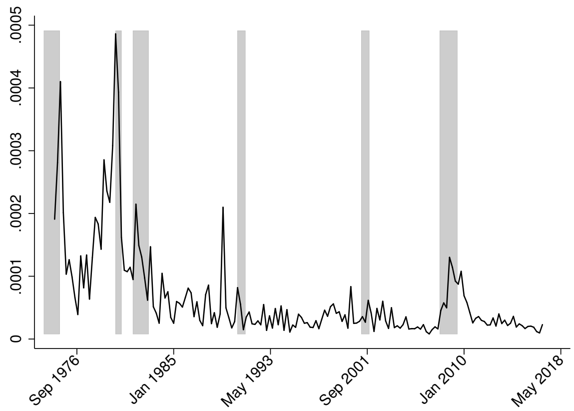

Figure: A

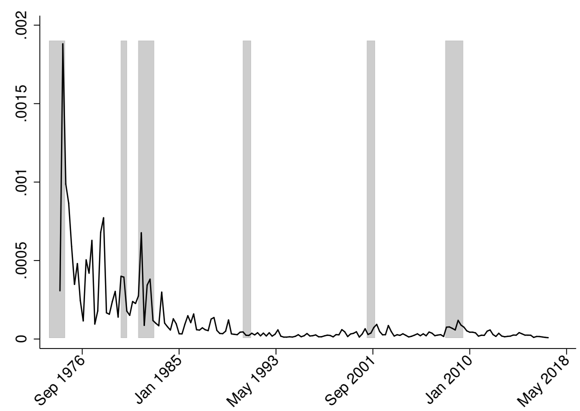

Figure: B

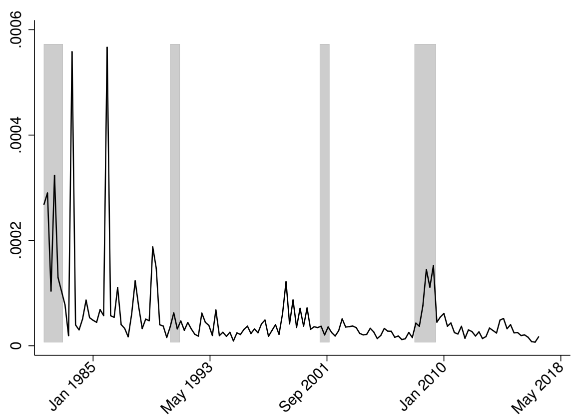

Figure: C

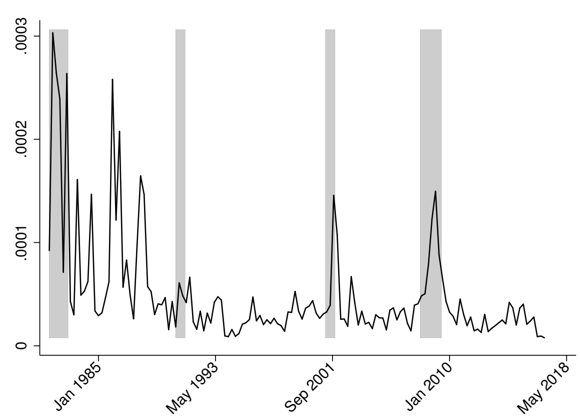

Figure: D

Continue on next page.

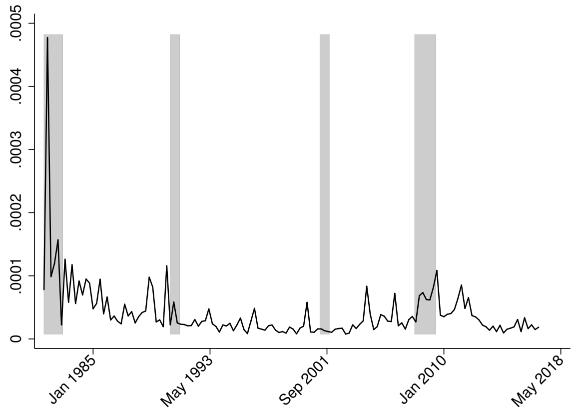

Figure: E

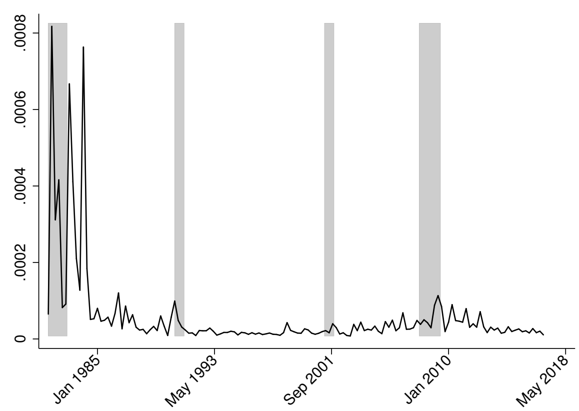

Figure: F

Note: These graphs display the time-varying uncertainty measures in all our macroeconomic variables. A and B show the Good respective Bad uncertainty about the Real GDP growth, C and D show the Good respective Bad uncertainty about the Real Personal Consumption growth. Graph E and F shows the Good and Bad uncertainty about the Inflation. Dark grey shaded areas are U.S. recessions as defined by NBER.