Explaining macro economic changes using credit spreads

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Abstract

In this paper the usefulness of credit spreads to explain changes in macro economic variables is tested. Several new credit spread indices are created, some of them taking maturity mismatching into account. These indices will be compared to the GZ index, created using the bottom-up approach as in Gilchrist,Zakrajšek (2012). The results of these new indices even exceed that of the GZ index, while requiring less information to be constructed. Lastly, the different indices will be combined to make a single model that outperforms all the previous ones.

Key words: Credit spreads, macro economic variables, maturity mismatching, predicting macro economic changes

Contents

1 Introduction

In the last decade, the US economy experienced the largest recession since the Great Depression. During this period, credit spreads turned out to be a crucial measure for the faith in the financial system. In addition, movements in credit spreads were thought to contain important information regarding the evolution of the real economy. This view is supported by the insights from the large literature on the predictive content of credit spreads.

The predictive ability of credit spreads is motivated by theories that are not in the accordance with the theory of Modigliani and Miller(1958). These theories state that the quality of borrowers' balance sheets is linked to their access to external finance. For example, a deterioration in the capital position of a bank, leads to a reduction in the supply of credit, which causes an increase in the cost of debt. And thus a widening of credit spreads and a reduction in spending and production in the real economy.

Challenging about predicting macro economic variables by using credit spreads, is the problem of maturity mismatching. One could for example simply take the spread of corporate bonds and government bonds. But than you have to make sure that the maturities of the bonds match. By just calculating a spread without considering the maturities of bonds, the created credit spread index will be of less predictive value. In Gilchrist et al (2009), a new method to eliminate the maturity mismatch in a credit spread index is introduced. However, for this method there should be data available on a micro level. For example, the secondary market prices of the bonds belonging to the credit spreads. Without this information this bottom-up approach as introduced in Gilchrist et al (2009) cannot be followed. Therefore, I come up with a different approach to get rid of the maturity mismatch in credit spread indices, by dividing the credit spreads into different maturity categories. Thereby a large part of the maturity mismatch will be eliminated.

I compare the results of this method with the results of the bottom-up approach as in Gilchrist, Yankov, and Zakrajšek (2009). This is done by comparing the in sample R^2 of the different models using a moving and a fixed window.

Remarkable is that this new index outperforms the 'GZ' index, as created in Gilchrist Zakrajšek (2012). This is noteworthy, because the idea behind the bottom up approach is that the maturity mismatch gets eliminated completely. In my new credit spread indices I just try to reduce the maturity mismatch. Still my approach seems more effective than eliminating the maturity mismatch completely as in Gilchrist Zakrajšek (2012). Several possible explanations for this are given.

I also create other credit spread indices, using the information of the credit spreads in different ways, such as a BBB-AAA spread. Hereby I also take maturity mismatching into account. These new indices, where the maturity mismatch is partly eliminated, perform significantly better in explaining macro economic changes than simple indices, where maturity mismatching is not taken into account.

In the end I come up with a combined model, which contains credit spread indices created with different methods. This model outperforms every previous model and is a very good model to explain macro economic changes by using credit spread indices. Thus, credit spreads indeed contain a lot of important information regarding the evolution of the real economy. In this paper the information is extracted from the credit spreads in several ”smart” ways. The methods used and the conclusion of this paper can for example be useful for central banks to forecast the economic outlook of a country, or for investors in for instance real estate.

2 Methods

2.1 Data

The dataset I use, is the same as in Nozawa (2012). The dataset contains the monthly credit spreads, maturity, date and credit rating for 39,120 different USA corporate bonds with 1,667,849 observations over the period janury 1973 - december 2012. The credit spreads are calculated as the difference of the yield of the bond and the estimated yield of a treasury bond with the same maturity. The yield of the treasury bond with the matching maturity is estimated by interpolation, using cubic splines. For more information see Nozowa (2012).

This dataset contains measurement errors, with unrealisticly high and low credit spreads as a consequence. First I drop all negative credit spreads since these are not realistic. Then I filter out the extreme observations by dropping every observation that exceeds the 97th percentile. After this procedure, there are 1,417,613 observations of 36,878 bonds left. The summarizing statistics are given in table 1.

Table 1: Summarizing statistics of the credit spreads after cleaning the data. τ in years.

rating	# observations	maturity	#observations
AAA	285369	Superlong $(15 < \tau)$	106994
A	388602	Long $(7 < \tau \leq 15)$	636648
BBB	355052	Medium $(3 < \tau \leq 7)$	486228
Junk	388590	Short $(0 < \tau \leq 3)$	187743

The following macro economic variables are taken from from the Federal reserve economic database (FRED) :

- The monthly private non-farm payroll employment (thousands of employees).
- The monthly civilian unemployment rate (percent)
- Manufacturing industrial production index (2007=100).

Also, the following spreads and rates are taken from the Federal reserve economic database:

- Real federal funds rate (in percent)
- Term spread (3-month Treasury yield less 10-year Treasury yield) (in percentagepoints)
- Commercial paper treasury-bill spread. The spread between the yield on 1-month A1/P1-rated non-financial commercial paper and the 1-month Treasury yield (in percentage points).

2.2 Credit Spread Indices

In this paper I develop several credit spread indices. Some of these indices account for maturity mismatching, some of them do not.

2.2.1 Arithmetic Mean with Maturity Mismatch

First I create a regular credit spread index, without taking the maturity mismatch into account. I do this by just taking the arithmetic mean of the credit spreads for every time period. Thus:

$$CSI_t^{simple} = \frac{1}{N_t} \sum_{i=1}^{N_t} cs_{i,t}. \tag{1}$$

Where $cs_{i,t}$ is the credit spread of bond i at time t. And N_t is the number of bonds at time t.

2.2.2 BBB-AAA spread with maturity mismatch

To calculate the BBB-AAA spread, I first divide the bonds according to their ratings. Then I calculate the arithmetic mean of the monthly credit spreads for the AAA and the BBB rated bonds separately:

$$CSI_t^{AAA} = \frac{1}{N_t^{AAA}} \sum_{i=1}^{N_t^{AAA}} cs_{i,t}^{AAA}. \tag{2}$$

$$CSI_t^{BBB} = \frac{1}{N_t^{BBB}} \sum_{i=1}^{N_t^{BBB}} cs_{i,t}^{BBB}. \tag{3}$$

Then the BBB-AAA spread is calculated by just subtracting the credit spreads from each other for every t.

$$CSI_{t,}^{BBB-AAA} = CSI_t^{BBB} - CSI_t^{AAA}. \tag{4}$$

2.2.3 Eliminating the Maturity Mismatch

In Gilchrist, Zakrajšek (2012), the secondary market prices of the bonds are available. Thereby the cash flows of a corporate bond can be calculated. Now a non-existing risk free bond, with exactly the same cash flows, can be created by:

$$P_{i,t} = \sum_{s=1}^{S} C(s)D(t_s) \tag{5}$$

Where $D(t) = e^{-r_t t}$ is the discount function with r_t the riskfree rate at time t. Now one can simply calculate the spread of the yields of the corporate and the risk free rate bond, which will not contain a maturity mismatch.

However, since I do not have the secondary market prices of the corporate bonds, I cannot eliminate the maturity mismatch this way. Therefore I circumvent this problem by dividing the maturities into different categories and only calculate spreads from bonds within the same maturity category.

2.2.4 Arithmetic Mean without Maturity Mismatch

For this index I divide the bonds into 10 maturity categories, with a length of 3 years each. Now I calculate the arithmetic mean again for every category:

$$CSI_{t,j}^{category} = \frac{1}{N_{t,j}} \sum_{i=1}^{N_{t,j}} cs_{i,t,j}. \tag{6}$$

Where j is the maturity category.

Some categories miss credit spreads for a few dates. I estimate these values by linear interpolation. If the first value (at January 1973) of a certain category is missing, I take the average of the value of the two credit spreads of the surrounding categories as the credit spread for that date. Except for the first and last category, there I just take the first value of the respectively next and previous category. For a missing last value of each category, the same method is applied.

To now calculate the arithmetic mean again, would in a sense bring the maturity mismatch partly back in the index and a lot of information regarding the maturities will be lost. Therefore I choose to use the different categories as separate independent variables, and not combine them to a single index. Note that due to this approach multicollinearity may arise. This because the different categories can be highly correlated.

2.2.5 BBB-AAA Spread without Maturity Mismatch

Here the same idea of dividing the data into maturity categories is applied. But now I choose to use fewer maturity categories (5), with a length of 6 years each. Otherwise there would be many dates in each category without a credit spread. Estimating these values by interpolation would cause too much deviation from the real values. There are 2 ratings (AAA and BBB) and 6 maturity categories, which gives 12 categories in total. Then I calculate the arithmetic mean for every category by:

$$CSI_{t,j}^{AAA} = \frac{1}{N_{t,j}^{AAA}} \sum_{i=1}^{N_{t,j}^{AAA}} cs_{i,t,j}^{AAA} \tag{7}$$

$$CSI_{t,j}^{BBB} = \frac{1}{N_{t,j}^{BBB}} \sum_{i=1}^{N_{t,j}^{BBB}} cs_{i,t,j}^{BBB} \tag{8}$$

Where j is one of the 6 maturity categories. Now I calculate the BBB-AAA spreads, by taking the difference of the BBB and AAA spreads of the corresponding categories.

$$CSI_{j,t}^{BBB-AAA} = CSI_{j,t}^{BBB} - CSI_{j,t}^{AAA}. \tag{9}$$

Where j is one of the six maturity categories. Here, calculating the arithmetic mean would also bring back the maturity mismatch. So therefore I use the 6 different categories as separate independent variables and again do not weigh them up to a single index. Note that here also the problem of multicollinearity may arise.

2.3 Credit Spreads and Macro Economic Variables

To determine the predictive ability of credit spreads for macro economic activity, I estimate the following univariate forecasting specification. This specification is the same as in Gilchrist and Zakrajšek(2012). This way the results can easily be compared to each other.

$$\nabla^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \nabla Y_{t-i} + \gamma_1 TS_t + \gamma_2 RFF_t + \sum_{k=1}^{K} \gamma_{2+k} CSI_{k,t} + \epsilon_{t+h} \tag{10}$$

In this equation $\nabla^h Y_{t+h} = \frac{c}{h+1} ln(\frac{Y_{t+h}}{Y_{t-1}})$ Where C is chosen to be 1,200 as a scaling factor for monthly data.

TS_t is the term spread (slope of the yield curve) at time t. RFF_t is the real federal funds rate at time t, $CSI_{k,t}$ is the kth credit spread index at time t and ϵ_t is the error term at time t. This equation gives the possibility to estimate the marginal information content of the different credit spreads on the federal funds rate and the term spread. The number of lags is chosen by minimizing the Akaike information criterion (AIC). The equation is estimated by ordinary least squares. h will is chosen at 3 and 12. This gives the possibility to forecast three and twelve months ahead.

2.4 Estimating with a Moving Window

In the section above, equation 10 is estimated once over the complete sample. There it is not taken into account that the coefficients are unstable over time. This can be shown by for example a CUSUM test. Therefore I now estimate the equation by OLS, using a moving window. The window is chosen at 120 months. The number of lags is the same as before, thus chosen by minimizing the Akaike information criterion over the complete sample.

2.5 Combined Model

Finally I combine all the credit spread indices to make a final model that should outperform each of the other models before. The model specification is the same as before:

$$\nabla^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \nabla Y_{t-i} + \gamma_1 TS_t + \gamma_2 RFF_t + \sum_{k=1}^{K} \gamma_{2+k} CSI_{k,t} + \epsilon_{t+h} \tag{11}$$

Where K is 20. This is because the model contains 10 catagory spreads, 6 BBB-AAA catagory spreads, the BBB-AAA spread without taking maturity mismatching into account, the arithmetic mean with the maturity mismatch, the CP-billspread and the GZ spread. The number of lags are again chosen by minimizing the Akaike criterion over the complete sample. This model is also estimated with a moving window because of the unstable coefficients over time.

Because of the large amount of variables and high correlation among them, some estimations of the coefficients differ insignificantly from zero. These variables are not left out of the model. This way, the comparison based on the in sample adjusted R^2, between this and previous models can be made fairly.

3 Results

3.1 Estimating over the Complete Sample

To check the goodness of fit, I calculate the in sample adjusted R^2 for each model. These values are given in table 2 and 3. The baseline specification is the model only containing the lags, the Term spread and the Real federal funds rate. Cp-bill spread is the model where the difference between the Commercial paper and the treasury bill paper as a spread is added as credit spread index. The GZ spread is the credit spread as calculated in Gilchrist, Zakrajšek (2012). Thus also created with their dataset. The simple spread is the spread calculated as in the section arithmetic mean with maturity mismatch. The category spread is the spread calculated as the arithmetic mean without maturity mismatch. The BBB-AAA spread is the BBB-AAA spread without taking the maturity mismatch into account. The BBB-AAA catagory spread is the BBB-AAA spread adjusted for the maturity mismatch.

As can be seen in table 2 and 3, the growth of private (nonfarm) payroll employment is the dependent variable with the highest in sample fit. The change in the civilian unemployment rate comes next and finally the growth of the manufacturing industrial production.

More interesting is how the different models perform. It seems that the Cp-billspread has some additional explanatory power for every dependent variable of the three month ahead specification. However, for the 1 year ahead specification the Cp-billspread only seem to have some additional explanatory power for the Industrial production and the Unemployment rate. The increase in adjusted R^2 is less here than in the three months ahead specification.

The Baa-Aaa spread seems to have only a very modest contribution to the goodness of fit. Especially in the case of the 12 months ahead forecast the contribution seems to be negligible. The GZ spread has a very high explanatory power

Table 2: The adjusted R^2 for the different models calculated over the whole sample for the three months ahead specification.

	Payroll Empl.	Industrial prod.	Unempl. rate
Proxy model	0.622757	0.268822	0.335964
Cp-bill spread	0.639228	0.331027	0.379709
Baa-Aaa spread	0.626356	0.297950	0.362315
simple spread	0.662643	0.323732	0.375310
GZ spread	0.689048	0.379591	0.425968
Catagory spread	0.674868	0.345265	0.421122
BBB-AAA spread 1	0.630393	0.308161	0.378636
BBB-AAA catagory	0.657064	0.330373	0.439051

Table 3: The adjusted R^2 for the different models calculated over the whole sample for the twelve months ahead specification.

	Payroll Empl.	Industrial prod.	Unempl. rate
Proxy model	0.421403	0.211492	0.270737
Cp-bill spread	0.424184	0.242035	0.292520
Baa-Aaa spread	0.421602	0.209795	0.273030
simple spread	0.455765	0.295334	0.353108
GZ spread	0.584956	0.340985	0.418493
Catagory spread	0.621789	0.428533	0.487454
BBB-AAA spread	0.420169	0.220547	0.295141
BBB-AAA catagory spread 2	0.462194	0.243003	0.349129

for every dependent variable in both time frames. For example in the case of the payroll employment with a time frame of one year, the GZ spread adds more than 16% to the adjusted R^2, compared to the baseline model. The results of the category spread are comparable with the results of the GZ spread. Remarkable is that the category spread underperforms the GZ spread for every dependent variable with a short term time frame. But for a time frame of one year, the category spread outperforms the GZ spread for every dependent variable. Both the GZ and the category spread perform significantly better than the simple spread for every dependent variable and in both time frames.

Finally the BBB-AAA spread with the maturity mismatch performs similar to the Baa-Aaa spread. But the BBB-AAA spread outperforms the Baa-Aaa spread in the time frame of one year. And vice versa for the three month timeframe.

The BBB-AAA category spread outperforms the regular BBB-AAA spread and the Baa-Aaa spread in every situation. In this case reducing the maturity mismatch has a very positive influence on the explanatory power.

3.2 Estimating with a Moving Window

The most interesting is how my spreads perform compared to the non category spreads. Therefore I show how the category spread performs compared to the GZ spread and the simple spread. And how the BBB-AAA catagory spread performs compared to the regular BBB-AAA spread. The in sample adjusted R^2 for these different models are given in figure 1, 2 and 3. The adjusted R^2 for the baseline specification is also given in these figures. In all figures are shaded areas, implying a US Economic Recession for that time period. These dates are set according to the National Bureau of Economic Research (NBER).

In figures 1, 3 and 5 it is very clear that the category spread has the highest R^2. The baseline specification has, as expected, the lowest R^2 on average. Notice that all models perform at their best at the end of the time frame. Especially for the Industrial production and the Employment rate this effect is very pronounced. Also every model has a low in sample fit in the period around 2000 and in the beginning of the sample period. As expected, the BBB-AAA category spread outperforms the regular BBB-AAA spread almost everywhere, implying that eliminating the maturity mismatch is successful here. Also the GZ spread is outperformed by the category spread almost everywhere, which is remarkable since the GZ spread should contain less duration mismatch than the category spread. The simple spread is outperformed by the GZ spread and by the Category spread. This implies that eliminating the maturity mismatch is very successful in these two models.

In times of financial crisis the models seem to perform above average, and just before a crisis the models seem to perform below average. This can be explained

Figure 1: The R^2 of the different models for the payroll employment with the three months ahead specification. Estimated with a moving window of 10 years.

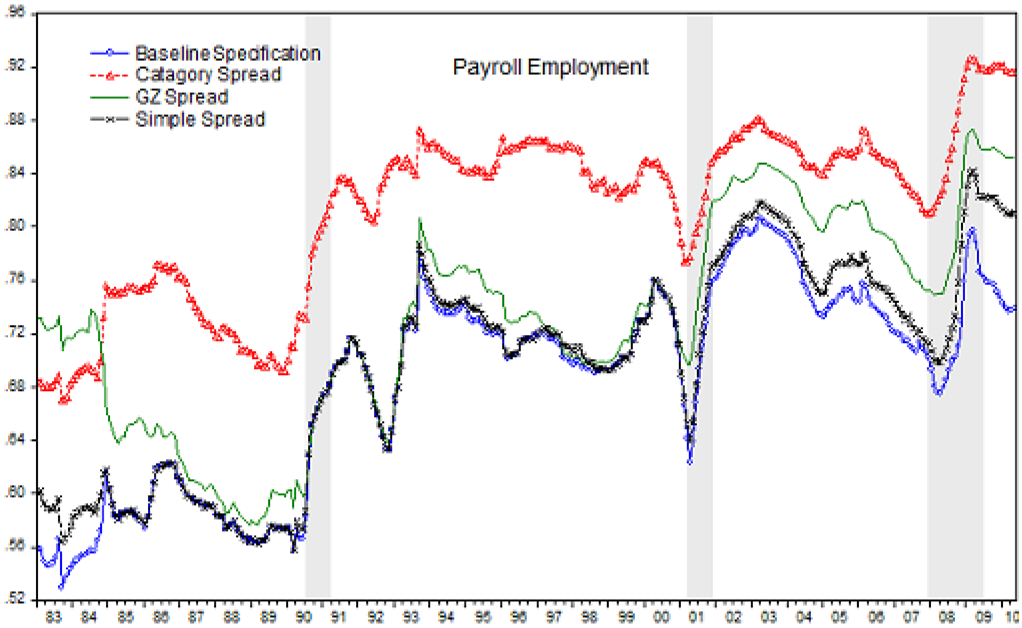


Figure 2: The R^2 of the different models for the payroll employment with the three months ahead specification. Estimated with a moving window of 10 years.

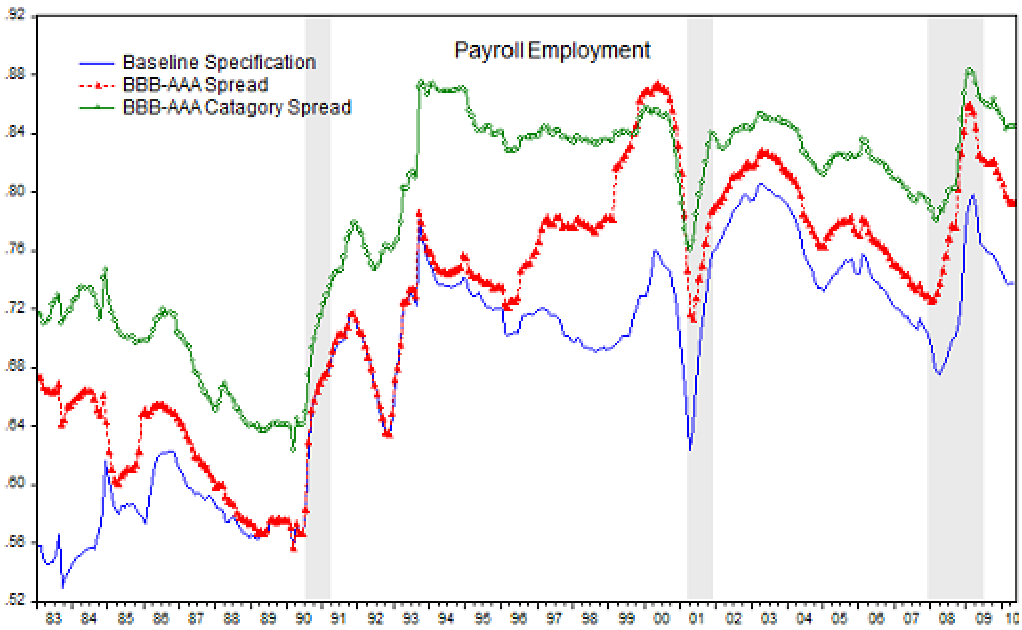


Figure 3: The R^2 of the different models for the industrial production Index with the three months ahead specification. Estimated with a moving window of 10 years.

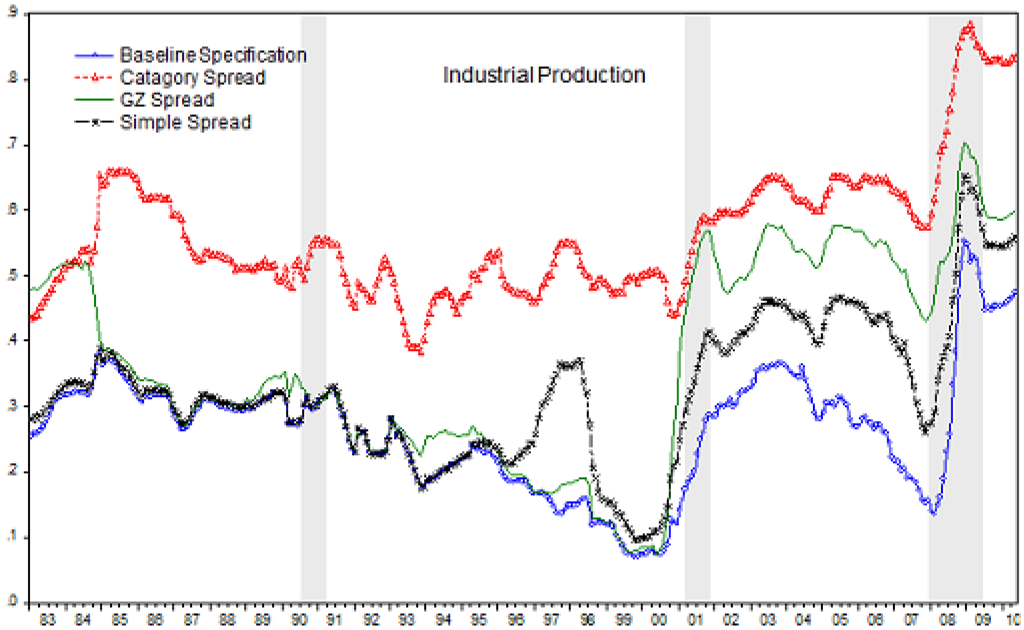


Figure 4: The R^2 of the different models for the industrial production Index with the three months ahead specification. Estimated with a moving window of 10 years.

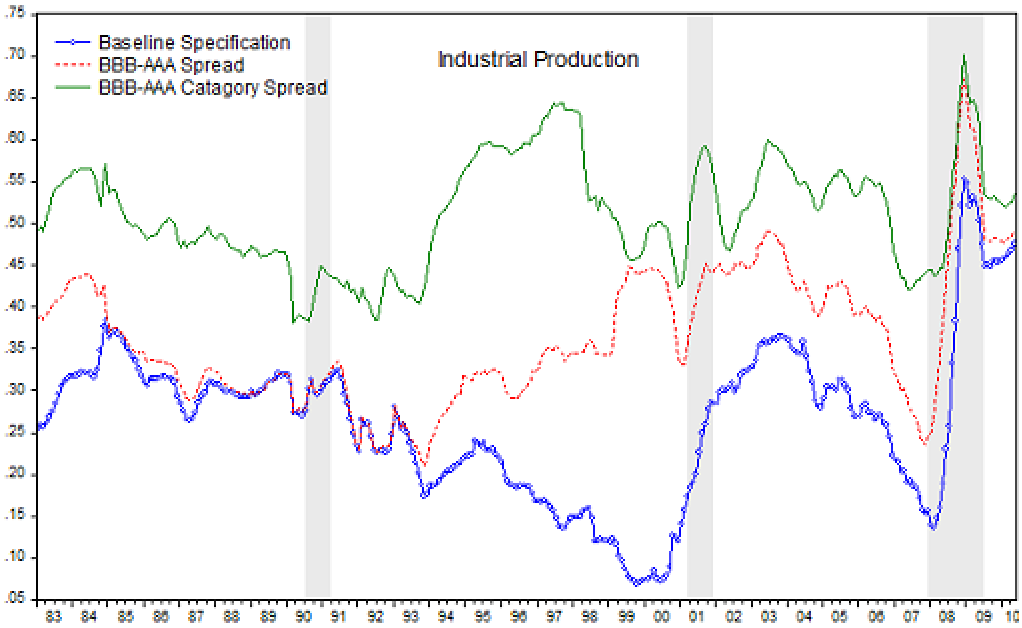


Figure 5: The R^2 of the different models for the unemployment rate with the three months ahead specification. Estimated with a moving window of 10 years.

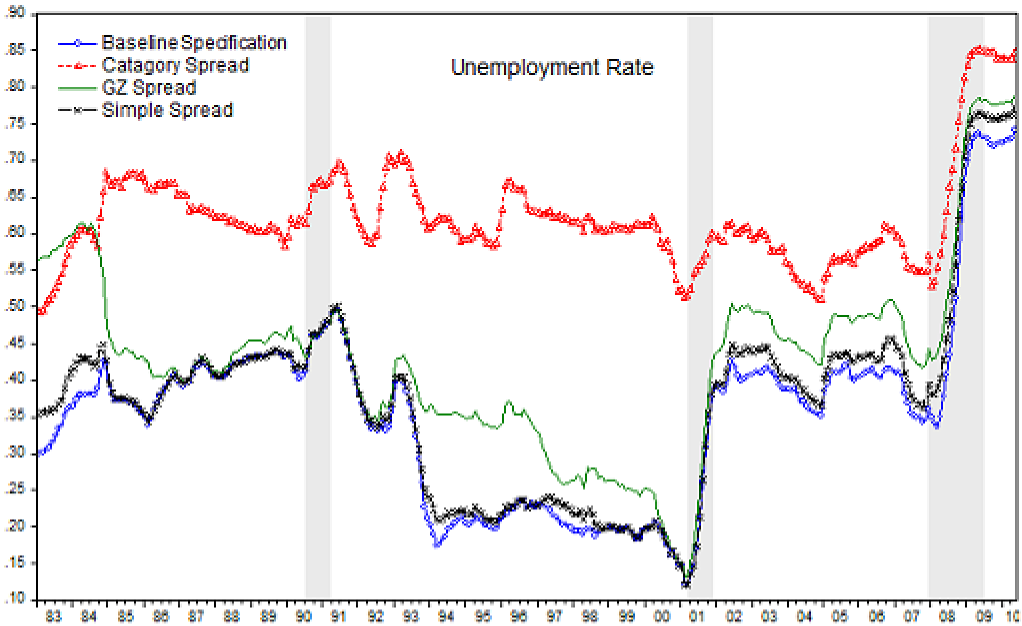
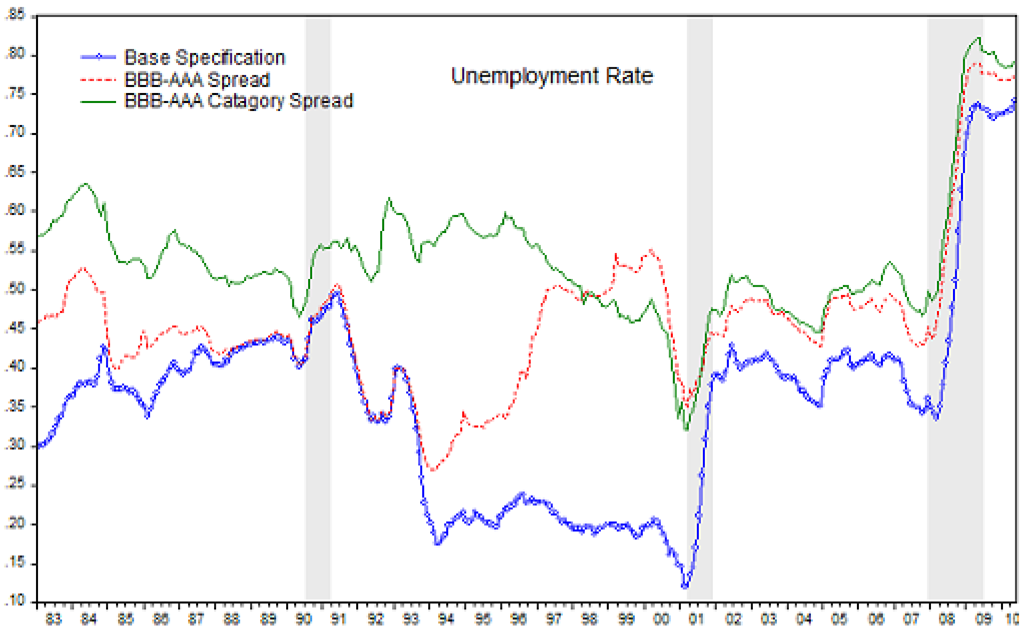


Figure 6: The R^2 of the different models for the unemployment rate with the three months ahead specification. Estimated with a moving window of 10 years.

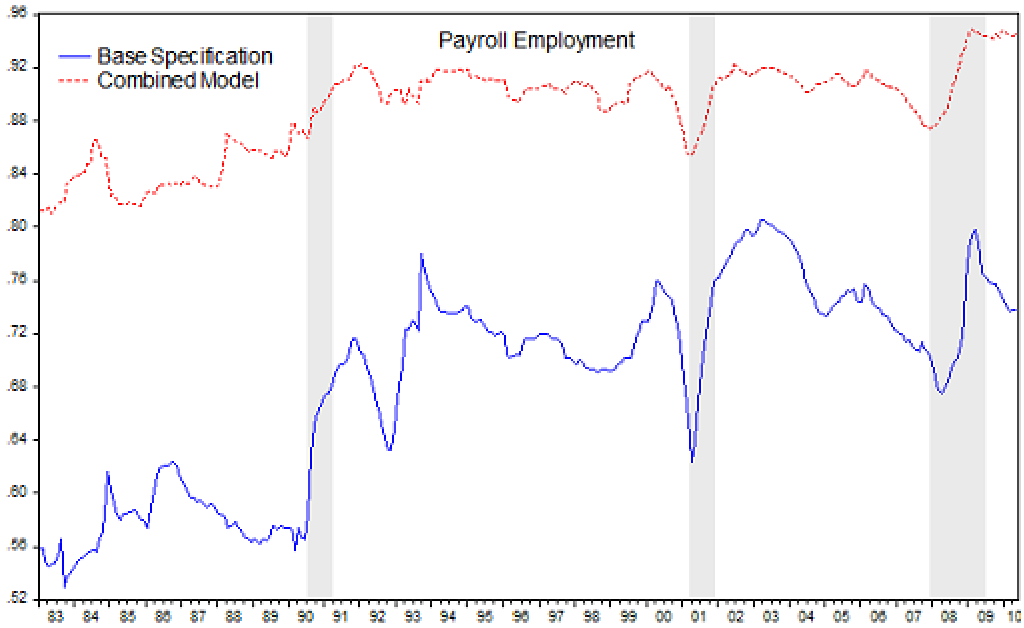


by the autoregressive(AR) components in the models. Just before a crisis, macro economic variables often oscillate, which is hard to capture with the AR components. During the crisis macro economic variables keep declining, which can easily be captured by the AR components. This effect results in respectivaly a low and high adjusted R^2.

3.3 Combined Model

The adjusted R^2 of the combined models and the base models for a time period of one quarter ahead are given in figures 7, 8 and 9.

Figure 7: The R^2 of the baseline and combined model for the payroll employment. Estimated with a moving window of 10 years.



The combined models have a significantly higher adjusted R^2 throughout the entire sample. Noticeable again, is the performance of the models just before and during a crisis. This effect can again be assigned to the AR components.

Figure 8: The R^2 of the baseline and combined model for the industrial production. Estimated with a moving window of 10 years.

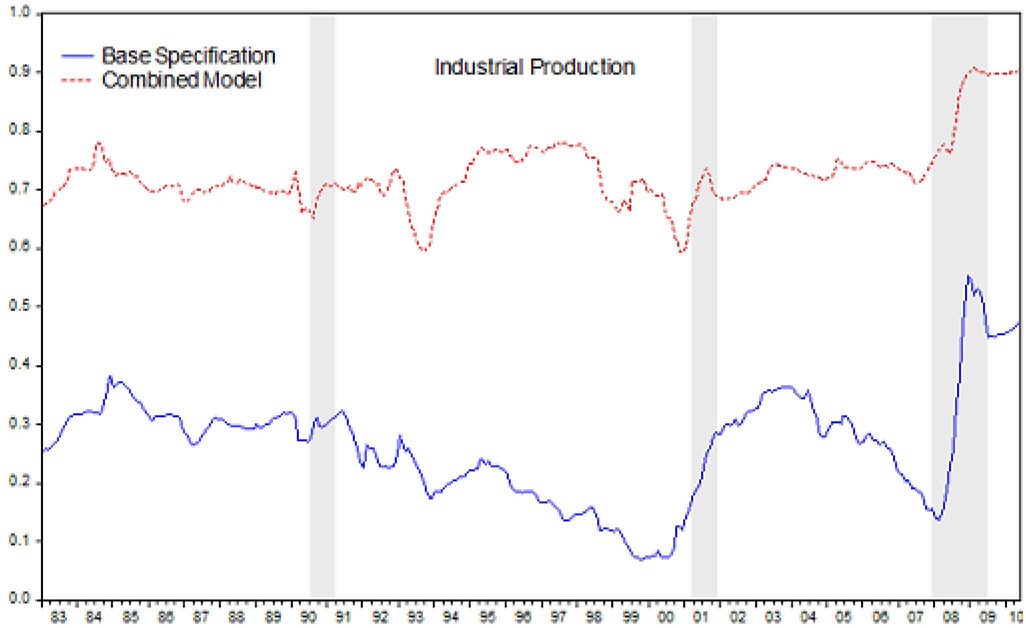
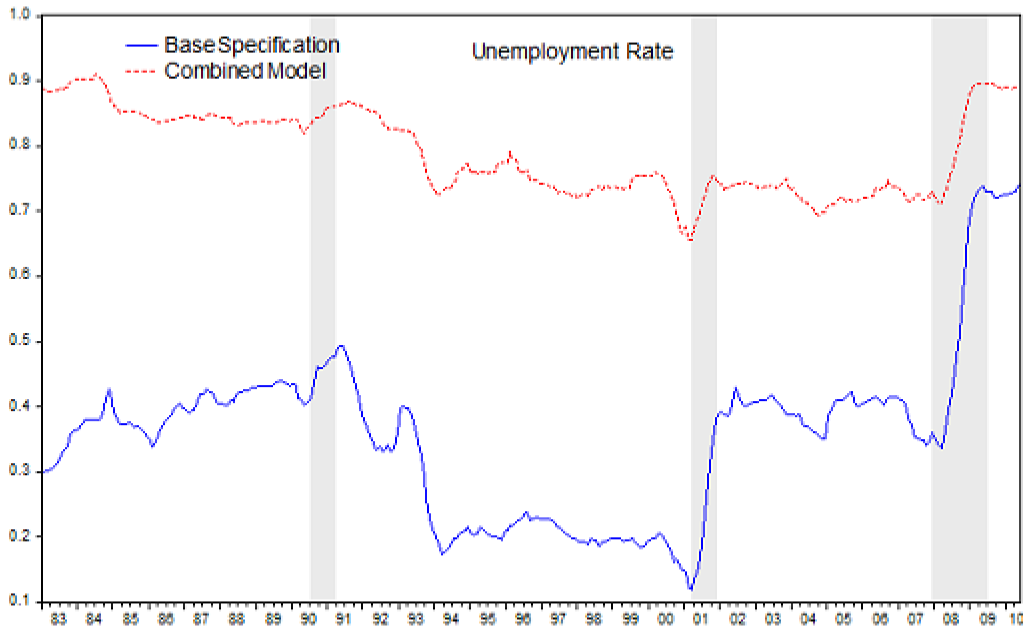


Figure 9: The R^2 of the baseline and combined model for the unemployment rate. Estimated with a moving window of 10 years.



4 Conclusion

Based on table 2 and 3, I can state that eliminating the maturity mismatch in the category spread and the BBB-AAA category spread is very successful. The adjusted R^2 for these models are significantly higher than for the simple spread and the regular BBB-AAA spread. Also, figures 1 through 6 show that the elimination of the duration mismatch is very successful. Very interesting to see in table 2 and 3, is that the GZ spread performs better than the category spread using the three month specification and worse for the 12 month specification. But figures 1, 3 and 5 show that with a moving window approach, the GZ performance is far worse than the performance of the category spread. And often even worse than the BBB-AAA category spread, which can have several causes.

First of all, I use a different dataset than in Gilchrist, Zakrajšek (2012). I use 1,417,613 observations. In Gilchrist, Zakrajšek (2012) only 346,126 observations are used. Also, in Gilchrist, Zakrajšek (2012) they have limited their sample to only senior unsecured issues with a fixed coupon schedule. To verify if this is the main cause of the huge difference in the results, my methods should be applied to the dataset they use.

Another explanation is that the bottom-up approach as created in Gilchrist, Zakrajšek (2012) is not as affective as creating a credit spread index by just dividing the credit spreads into maturity categories. This could have a connection with the fact that I do not weigh my separate categories into a single index. This way least squares determines different coefficients for each category. This results in completely different coefficients for the separate categories.

Very interesting is that their bottom up approach works well when estimating over the complete sample, but when using a moving window, their method is outperformed by my method almost everywhere. This can also be subscribed to the fact that I use 10 categories and do not weigh them into one index. The correlations among the different categories estimated over the complete sample are in Appendix A. The correlations of the first category with the rest estimated using a moving window is in Appendix B. Here it is very clear to see that in the sub samples of the moving window approach, the correlation among the different categories is less than in the complete sample. Thus, when using a moving window, the categories are less correlated and all together contain more information. This way the information that each category contains, can be used more efficiently than in the case of estimating over the complete sample. This explains the significant increase in the R^2 when using a moving window of my models compared to the GZ model.

In my paper I have not adjusted my models for multicollinearity, because I was only interested in the in sample adjusted R^2. Using these models to make actual forecasts can give problems because of the large variance of the coefficient estimations. This can even make these models useless. In this case I would recommend to use fewer categories to reduce the correlation among the independent variables. Another possibility is to weigh the different categories into a single index.

Combining all the individual models is a very successful method to increase the explaining performance. The in sample adjusted R^2 is a lot higher than in the case of the individual models, and the combined model seems to perform far more constant over time than the individual models, making the combined model less vulnerable for exceptional situations. Still the decrease in R^2 just before an economic crisis is visible in the combined models for all three dependent variables. A decrease in the R^2 implies that forecasting such events using credit spreads is very difficult. However, looking at the complete sample, I can state that explaining changes in macro-economic variables by using credit spreads is very successful.

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5 Appendices

5.1 Appendix A

Table 4: The correlation coefficients of the 10 different categories over the complete sample.

category	1	2	3	4	5	6	7	8	9	10
1	1,000	0,936	0,870	0,818	0,845	0,864	0,858	0,715	0,591	0,624
2	0,936	1,000	0,939	0,867	0,858	0,896	0,896	0,778	0,659	0,637
3	0,870	0,939	1,000	0,925	0,838	0,846	0,890	0,820	0,691	0,691
4	0,818	0,867	0,925	1,000	0,880	0,819	0,884	0,783	0,696	0,719
5	0,845	0,858	0,838	0,880	1,000	0,834	0,841	0,636	0,584	0,616
6	0,864	0,896	0,846	0,819	0,834	1,000	0,903	0,742	0,623	0,656
7	0,858	0,896	0,890	0,884	0,841	0,903	1,000	0,813	0,700	0,710
8	0,715	0,778	0,820	0,783	0,636	0,742	0,813	1,000	0,890	0,842
9	0,591	0,659	0,691	0,696	0,584	0,623	0,700	0,890	1,000	0,890
10	0,624	0,637	0,691	0,719	0,616	0,656	0,710	0,842	0,890	1,000

5.2 Appendix B

Figure 10: The correlation of the first category with the 9 other categories. Estimated using a moving window of 120 months.