STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
Master's Thesis

Corporate Bond Spreads as a Predictor of Euro Area GDP

Testing the Financial Accelerator at the Sector Level

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ABSTRACT

We study the predictive power of corporate bond spreads over real economic activity within the framework of the financial accelerator theory. Previous research has confirmed this relationship but there is a gap in the literature concerning classifications of corporate bonds other than credit rating and bond maturity. To fill the gap, our purpose is to test whether the financial accelerator can be detected at a sector level and if some sectors contain more predictive power than others. We conduct an in-sample regression analysis and an out-of-sample forecast using data from the euro area. Our main results confirm that corporate bond spreads hold predictive power over real GDP growth on a sector level, verifying the financial accelerator, but the relationship is highly dependent on the time horizon one wants to foresee.

Keywords*:* Financial accelerator, credit risk, corporate bond spreads, external finance premium, forecasting, euro area

Tutor: David Domeij
Examiner: Mats Lundahl
Discussants: Erik Segerborg and Mikael Söderström

Presentation: 9 June 2010, 13.15 – 15.00, room 342

Acknowledgements: We thank Tore Ellingsen and Rickard Sandberg for their support and valuable advice.

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Table of Contents

1. Introduction

It is today widely accepted that a well functioning financial system is an important ingredient to creating a prospering society. As highlighted by the chairman of the US Federal Reserve, Mr Ben Bernanke, real factors such as workforce productivity, quality and quantity of capital stock, technology, creativity and ideas – no matter how good – may still fail if a project lacks financial capital. To reach its full potential, both firms and households are in need of an efficient and reliable financial system.[1]

Although macroeconomic models traditionally use strict perfect-market assumptions to ignore market imperfections that can disable an efficient system, most academics and economists of today would acknowledge their existence. One of these imperfections is the problem of asymmetric information between market participants, which seems to feed into the market psychology, leading financial markets into both sky-high overconfidence and sudden sheer panic. During the past few decades, it has become increasingly popular not only to look at the connections between the financial markets and real activity, but also how the former may predict the latter. If a good financial system is so important for a country's economic development, shouldn't we be able to look at the state of the current financial market and see what may be in store for the economy in the future?

Financial markets are forward-looking markets where new information replaces old in a matter of seconds. Prices of financial products such as stocks, bonds and derivatives change continuously to incorporate new information about the future prospect of their profitability. Looking at economic variables such as GDP and industrial production on the other hand, data is collected with lower frequency and when finally published, it is already part of yesterday's news. Finding a link between the two markets in which we could use financial-market data to predict economic variables is understandably an appealing objective for both academics and policy-makers.

Several financial variables such as interest rates, term spreads, stock prices, and credit spreads have through the years been tested for predictive power over the business cycle. Stock and Watson (2003) provide an extensive overview of the literature and conclude that even though some of the variables have proven to be useful indicators, the relationships seem to vary between markets and

[1] These remarks were made by Ben Bernanke at a conference held at the Federal Reserve Bank of Atlanta in 2007, discussing the credit channel of monetary policy.

over time. A wide strand of this literature is the one looking at the corporate bond market and credit spreads searching for predictive power over the real activity.[2] With our paper we wish to contribute to this field of the research area.

The text-book definition of a credit spread, as described by Fabozzi (2010), is the difference in yield between a corporate bond containing default risk and a risk-free government bond, similar in all aspects but the quality of their issuer's financial health. In real life, the risk-free bond is usually exchanged for some sort of benchmark interest rate against which a corporate bond with the same maturity is compared. In the US, treasuries are commonly used as benchmark interest rates, but other types of low-risk interest rates such as yields on high-quality bonds can also be applied.[3] Rather than calling these spreads credit spreads, the name corporate bond spreads may be more appropriate. Regardless of how the spread is calculated, it reflects the fact that investing in corporate debt involves more risk than investing in government bonds and investors will thus require compensation in the form of a higher yield.[4] Furthermore, as investors are forward-looking, it will be reflected in today's required yield how the market expects the firm to perform in the future. The market's expectations will thus affect the firm's cost of capital and hence influence its investment and production decisions. Looking from a macroeconomic perspective, if recessionary tendencies hit the aggregate market, we would expect to see rising spreads across the corporate bond market. If this then leads to lower investment and production on a wide scale, the whole business cycle could be affected. The evolution of corporate bond spreads may thus be able to tell us something about the future economic environment. Bernanke, Gertler, and Gilchrist (1996) defined this relationship between the credit market and real economic activity in the theory of the financial accelerator. Since then, most studies analysing the link between corporate bond spreads and real activity have either tested the existence of the financial accelerator or used it to validate their research area.

To analyze whether corporate bond spreads contain predictive information, researchers have divided bonds into different credit-rating and bond-maturity segments, trying to find the best combination for forecasting real activity. To our knowledge, there has however not yet been any studies conducted using other classifications. As different types of firms presumably follow

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[2] Credit spreads can also be referred to as default spreads, yield spreads and corporate bond spreads.
[3] See for instance the research conducted by Chan-Lau and Ivaschenko (2001).
[4] To assist in the judgment of a bond's credit quality, several rating institutes provide credit ratings on a regular basis. The spectrum of credit ratings is divided into two segments, the investment-grade segment which includes high-quality bonds and the speculative (high-yield) segment which includes bonds of poorer credit quality, also known as the junk-bond segment. In *Appendix A,* we present an overview of the credit-rating scale provided by the credit rating agency Standard & Poor's.

different patterns in the business cycle, they are likely to react differently when economic shocks occur and thus affect real activity differently. An analysis studying firm-level characteristics of corporate bonds could thus further add to the understanding of the relationship between corporate bond spreads and real economic activity. With this paper, we aim to fill this gap in the literature by studying the relationship at the sector level, thus revealing whether the measure of the corporate bond spread used for forecasting purposes could be improved by dividing the spread into sectors of different characteristics.

The purpose of our work is to investigate whether;

i) the financial accelerator can be detected at a sector level, and
ii) if some sectors contain more predictive power than others.

Our analysis will be conducted in two steps. Firstly, the relationship will be studied through an in-sample regression analysis, and secondly, we will test the predictive power of the spreads through out-of-sample forecasting. The geographic market we choose to study is the one of euro-denominated corporate bonds and the measure of real activity we employ is euro area GDP. Compared to the market of dollar-denominated bonds, the euro market has not yet been as actively analyzed because of its relatively young age, but studies searching for predictive power have over the years been validated by the rapid growth and integration of the market.[5]

To achieve as noise-free and stable results as possible, we exclude the recent financial and economic crisis from our sample period. The vast amount of extreme observations presumably included in the data during the crisis could lead us to find relationships that in reality do not exist or vice versa. After conducting our analysis we will however extend the sample period to include the crisis in order to evaluate the usefulness of our model within economically unstable environments.

The paper has been structured as follows. In section 2, we provide the reader with a theoretical background covering the financial accelerator and a summary of important findings in previous studies. In section 3, we describe the methodology of our analysis, covering time-series issues in general and our model in specific. The data chosen for our work can be found in section 4 and the results from our investigation will be described in section 5, followed by an analytical discussion in section 6.

[5] See for example De Bondt (2002) and the ECB report "The Euro Bond Market Study" (2004).

2. Theoretical Framework and Previous Research

The theoretical framework of our paper follows the theory of the financial accelerator, defined by Bernanke, Gertler, and Gilchrist (1996). The theory provides useful insights to how seemingly small and short-lived events can lead to large and more long-lasting economic swings, and is thus an important factor when studying the evolution of the business cycle.[6] Much of the research done in recent years with focus on how different credit-market asset prices can affect and possibly predict future real activity have referred to the financial accelerator and also provided results that acknowledge its existence. The most relevant of these studies will be presented under section *2.2 Previous Research*.

2.1 The Financial Accelerator

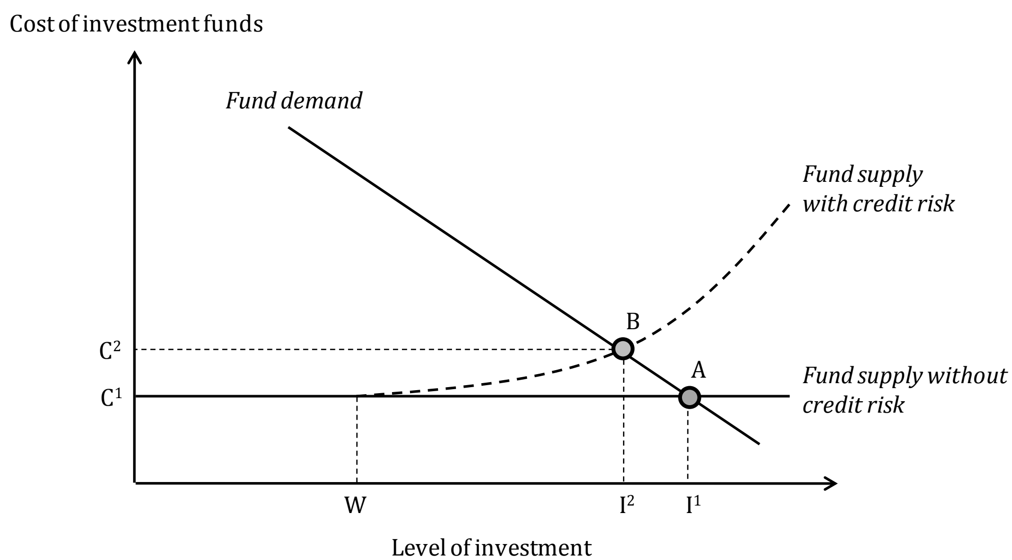
In contrast to traditional macroeconomic models, the theory of the financial accelerator does not assume a perfect market, instead it is based on the actual frictions of the market and how these can accelerate business cycle swings. The theory starts off in the financing choice of a firm, closely related to the well-known pecking-order theory of corporate finance which originates from the problem of asymmetric information. As defined by Brealey, Myers, and Allen (2006), the pecking order states that a firm looking to invest will prefer to use internal financing, such as retained earnings, rather than external financing, such as bond issuance, as the former is less costly. Since the borrower, or bond issuer, always will be better informed regarding its own ability to repay the loan in the future, the lender, or bond investor, will require a higher yield, a premium, to be compensated for the uncertainty. Bernanke, Gertler, and Gilchrist (1996) define the premium as an external finance premium (hereinafter EFP) that drives a wedge between internal and external financing costs and creates a deadweight loss. As the corporate bond spread is the difference between the required yield, i.e. the firm's cost of issuing bonds, and a risk-free rate, such as the alternative cost of using internal financing, the spread can be interpreted as a proxy for the EFP.

The size of the EFP varies among firms and over time and it is defined by Mody and Taylor (2004) as an endogenous variable that is inversely dependent on the balance sheet strength of the borrower. A financially healthy firm with high credit rating will be able to issue bonds at a much

[6] The theory of the financial accelerator is a vital part of the monetary transmission mechanism, covering both bank-based and credit-market lending. To suit the purpose of this paper we will, in line with several other authors in this field, focus on the part of the theory concerned with credit-market lending, i.e. the corporate bond market. See for example Gertler and Lown (2000), Chan-Lau and Ivaschenko (2001), Mody and Taylor (2004), and De Bondt (2004).

lower cost than a firm with low credit rating. As the financing cost is a central question in the investment choice, it is only logical to think of the EFP as a factor affecting the level of investment. As an illustration of how the balance-sheet strength, the cost of financing and the choice of investment level are related, De Bondt (2004) provides a graphical illustration, shown in *Figure 2.1*.

Figure 2.1. The External Finance Premium and the Financial Accelerator Mechanism



The horizontal line illustrates the supply of funds while the downward sloping line illustrates the demand for funds. If markets were perfect, i.e. no credit risk or asymmetric information, we would have an equilibrium at point A. The cost of external funds would then be equal to the cost of internal financing (C^1). When frictions such as credit risk and asymmetric information enters the picture however, investors will require additional compensation and the supply curve starts sloping upwards when the amount of financing exceeds the firm's net wealth (W). A new equilibrium is found in point B where the cost of investing is higher (C^2) and the amount of investment undertaken (I^2) is lower than in point A (I^1). The vertical distance between the two supply curves illustrates the EFP. As the EFP moves, so will the level of investment. If the firm's net wealth covers the amount of external finance attained for investment, the cost of these funds will still be equal to the cost of internal financing, simply because the balance sheet is strong enough to mitigate the repayment uncertainty.

Mody and Taylor (2004) describes the financial health of a firm as procyclical, i.e. it improves when the state of the economy improves. As there is an inverse relationship between the EFP and the firm's financial position, the EFP therefore becomes countercyclical, i.e. it falls when the state of the economy improves. This is the foundation of the financial accelerator. In a healthy economy, strong balance sheets will reduce the EFP, giving firms easy access to external financing which leads to increased firm activity. This in turns leads to even stronger balance sheets and an even lower EFP – and so the spiral continues. A falling EFP today will thus through the financial accelerator promote rising economic activity tomorrow.

In the same way as a boom is amplified though improving conditions in the financial markets, recessionary tendencies can spiral into a bust. Going from a boom, the economy will start to turn right at the time when the debt burden is the highest. As the financial health deteriorates, firms will no longer afford to keep the same level of debt and are forced to cut back on investment and production. Applying the financial accelerator theory, it is easy to understand how even the smallest increase in the EFP can have a considerable negative effect on future economic activity.

2.2 Previous Research

Studying the relation between asset prices and economic activity has over the years been done in a variety of ways, not only within the framework of the financial accelerator. Several different financial variables have been employed in the hopes of finding predictive power over different measures of real economic activity. Stock and Watson (2003) provide an extensive overview of the earlier research, and sum up to three main conclusions. Conclusions based as well on earlier literature, as on their own empirical tests using a wide range of different financial variables and measures of economic activity.

Firstly, Stock and Watson find that the predictive power of asset prices over real activity is statistically significant at some points in time in some countries, and the degree of explanatory power is the best when combining more than one asset price, findings which later on have been confirmed by several other authors. For example, Gertler and Lown (2000) strongly question the value of relying on one single variable for forecasting purposes, but if used prudently the authors believe that the power of a variable, in their case the corporate bond spread, can be of good use for policy makers. Stock and Watson secondly find the predictive power to be unstable over time, i.e. they find no proof that a variable serving as a good predictor in one time period will predict well in another. Thirdly, they conclude that the most commonly used significance test, the Granger causality test, does not perform well in predicting future results as it is based on in-sample forecasting. Overall, they argue that many of the empirical methods used in previous papers are not statistically defensible.

Numerous different variables have been researched for predictive power and one that has been in the centre of attention for many economists is the interest-rate term spread. One of the more well-known papers researching the term spread is written by Estrella and Hardouvelis (1991), who find that more than one third of the changes in future output was explained by their measure of the term structure using an in-sample OLS regression analysis.[7] During the 1990's, the relationship however seemed to be breaking down and several studies, for example those conducted by Estrella and Mishkin (1996) and Mody and Taylor (2004), empirically concluded that the term spread had lost its predictive power over real activity. Instead, many researchers now shifted their attention towards the credit markets and corporate bond spreads, where the financial accelerator theory came to play a central role.

Testing corporate bond spreads for predictive power over the business cycle has since the introduction of the theory of the financial accelerator been done in a variety of different ways. Although corporate bond spreads overall have proven to be useful predictors, there is disagreement between which type of spread predicts the best and which type of statistical model can best detect the relationship. Some argue that the speculative, or high-yield, segment of the market contains the most predictive content while others argue for the use of investment-grade bond spreads.[8] Gertler and Lown (2000) use high-yield bond spreads in the US as they believe these spreads to be the ones most clearly affected by the market frictions described in the theory of the financial accelerator. Their results suggest that the high-yield spread leads movements in the output gap one to two years ahead. Mody and Taylor (2004) also argue that high-yield corporate bond spreads are good predictors and find the strongest forecasting power on horizons ranging from three quarters up to one year.

In contrast, Chan-Lau and Ivaschenko (2001) argue that economic fundamentals are better reflected in investment-grade bond prices than in the high-yield alternative, and therefore argue that the former is more appropriate for this sort of research. In a recession they stress that while high-yield issuers would not be able to access the credit market, investment grade firms still have the possibility to find investors. Hence, the prices of investment-grade bonds will better reflect all different states of the economic cycle. They evaluate the relationship both in- and out-of-sample

[7] Estrella and Harouvelis define the term spread as the difference between the 10-year government bond rate and the 3-month T-bill rate.
[8] See A*ppendix A* for an overview of the different rating classes of credit spreads.

and find that the bond spreads predict marginal changes in industrial production in the US up to twelve months into the future.[9]

Some of the more recent studies searching for empirical evidence of the financial accelerator have been conducted by Mueller (2009) and Gilchrist, Yankov, and Zakrajsek (2009). Mueller performs an in-sample analysis and finds strong proof of corporate bond spreads over all rating classes being good predictors of real GDP growth in the US. In specific, he finds that corporate bond spreads have strong predictive power over GDP growth up to a horizon of three quarters and that a combination of different rating classes gives the highest goodness-of-fit. He also constructs an out-of-sample macro-finance term-structure model in order to further investigate what causes the relationship. One of his findings is that the spread is highly correlated with the index of tighter loan standards, a result that lies in line with the financial accelerator theory. Gilchrist, Yankov, and Zakrajsek also confirm the presence of a financial accelerator in the US but argues that corporate bonds of intermediate risk are the best for predicting purposes. Apart from confirming a general relationship between spreads and real activity, the two papers also observe an even stronger causality in times of high volatility.

The literature covering the European bond market is not as extensive, but interest has grown since the introduction of the single currency. Among the first to study the leading indicator properties of corporate bond spreads in Europe, prior to the single currency, were Davis and Henry (1994). Using data from the United Kingdom and Germany, they construct four different kinds of financial spreads where one is the corporate bond spread.[10] Using in-sample estimation models, they find evident that financial spreads jointly do contain information of future real GDP and other macro variables such as the public sector deficit, the real exchange rate and the current balance. Davis and Fagan (1997) also study the European bond market but include all EU countries in their analysis. However, their results argue against the existence of a financial accelerator, first and foremost because of the instability of the forecasting results over time.

Shortly after the introduction of the euro, De Bondt (2002) studies the market for euro-denominated corporate bonds belonging to the lower part of the investment-grade spectrum. In contrast to Davis and Fagan, he finds that these corporate bond spreads perform well in predicting

[9] Chan-Lau and Ivaschenko consider several different variables as benchmark rates when calculating their credit spreads, such as treasuries, agency securities, and AAA-rated bonds, and find spreads over treasuries to contain the most predictive power.

[10] Davis and Henry also study an interest-rate term spread and two types of spreads based on government bonds and equity.

output growth up to ten months into the future. He admits that the sample period for the euro area is short, but argues that the market is already liquid enough to contain useful macroeconomic information and he reaches the same conclusion using three different methods.[11]

A more recent study concerning the euro area was conducted by Buchmann (2009) who looks at both the high-yield and the investment-grade segments of the European corporate bond market. Buchmann wishes to add to the work previously done by De Bondt and tests whether there is a financial accelerator at work in the euro area. His results from running in-sample regressions support previous findings and he concludes that the predictive qualities are signs of the spreads being good proxies for the EFP. In line with the arguments put forward by Chan-Lau and Ivaschenko (2001), he finds that high-yield spreads seem to correlate with real activity rather contemporaneously, and therefore have little forecasting power. Investment-grade spreads, on the other hand, perform considerably better and Buchmann finds AA-rated spreads with a maturity of seven to ten years to explain an impressively 93 percent of the variation in output one year ahead.

Returning to Stock and Watson's (2003) discussion regarding inadequate econometric attention, they requested a wider awareness of the econometric issues related to time series data, especially when dealing with persistent variables such as GDP. Weaknesses relating to stationarity, overlapping observations, and model stability over time are still present in later research. We aim to address these issues in section *3. Methodology*.

To summarize, much of the literature in this area confirm that corporate bond spreads in general, and in Europe, the investment-grade segment in particular, are good proxies for the EFP and that the theory of the financial accelerator can help explain business cycle developments. However, the methods used in some papers are questionable from an econometrical point of view. Looking at the research already done, it is evident that much focus has been directed towards finding the optimal rating-class and maturity combination. By using another bond categorisation, we hope our work will contribute to the field of research.

[11] De Bondt defines output growth as the annual growth rates in real GDP and industrial production. The methods he uses are a Granger causality test, a simple regression, and an impulse-response function based on vector autoregressions.

3. Methodology

To investigate whether the widely accepted financial accelerator can be detected on a sector level, we use models inspired by Buchmann (2009) and Estrella and Hardouvelis (1991). Also we consider some of the caveats identified by Stock and Watson (2003).[12]

Our analysis will be conducted in two steps. First, we will perform an in-sample regression analysis to investigate the relationship between sector corporate bond spreads and GDP growth within our sample period, i.e. to test for the existence of a financial accelerator. Second, we will perform an out-of-sample forecast in order to evaluate whether some sector spreads contain more predictive power than others.

3.1 In-Sample Regression Analysis

As discussed by Stock and Watson (2003), analysing data that is observed and sorted over time can be problematic. Time-series data is often found to be correlated with its own past values, leading to biased estimates. As noted by Mueller (2009), this is true for GDP growth due to its persistence over time. To take this into account we will use autoregressive (AR) models, which are models in which lagged values of the dependent variable are included among the independent variables.[13] This type of model will not only correct the estimates for later forecasting errors but also reduce autocorrelation in the estimated standard errors.[14] We will employ two different AR(p) models using OLS regression analysis, one excluding and one including control variables;

$$y_{t,t+k} = \alpha + \beta SPREAD_t + \sum_{i=1}^{p} y_{t-i,t-i+k} + \varepsilon_t, \qquad (1)$$

$$y_{t,t+k} = \alpha + \beta SPREAD_t + \sum_{i=1}^{p} y_{t-i,t-i+k} + \sum_{j=1}^{N} \delta_j CONTROL_{j,t} + \varepsilon_t, \qquad (2)$$

where $y_{t,t+k}$ is the logged annualized cumulative percentage change in real GDP, from time t to t+k, with k representing the number of quarters, calculated as

$$y_{t,t+k} = \frac{400}{k} + \ln\left(\frac{GDP_{t+k}}{GDP_t}\right). \qquad (3)$$

[12] Mainly we follow the work of Buchmann, however his analysis is in some aspects weak, primarily due to the absence of control variables and a too high focus on adjusted R-squared levels (a measure that is known to be high in AR models as the lagged values of the dependent variable usually contain high explanatory power).
[13] Y is said to follows an AR(p) process when Y_t depends on its past values p time periods back in time expressed as $Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \cdots + \alpha_p Y_{t-p} + u_t$.
[14] Autocorrelation is defined by Gujarati (2003) as correlation between observations in a series ordered in time or space, and we will see this type of correlation in our estimated error terms ($\hat{\varepsilon}_t$).

We will also run a simple GDP model where $y_{t,t+k}$ is regressed against lagged values of itself only.[15] This will give us an indication of the added value from including corporate bond spreads.

We will look at the causal relationship between corporate bond spreads and GDP growth one to four quarters ahead (k=1, 2, 3, 4). The optimal number (p) of lagged GDP growth ($y_{t-p,t-p+k}$) in each regression will be determined by using the Akaike Information Criterion.[16] Although several different measures exist, according to Stock and Watson (2003) Akaike is the one most commonly used.

The corporate bond spread for each sector is defined as $SPREAD_t$ and is calculated as the difference between a sector corporate bond yield index and a benchmark interest rate, both with the same maturity. We will also include a general corporate bond spread covering all sectors in order to reassert previous research in which such a spread has been found to be a good proxy for the EFP.

In Model 1, we test for the presence of a financial accelerator in each sector by regressing $y_{t,t+k}$ against *SPREAD*. Each *SPREAD* will occur in four regressions, one for each GDP-growth horizon. As we expect a higher spread to have a negative impact on the future path of GDP, we expect the coefficients (β) to be negative. To argue for a statistically significant relationship between a specific sector and future GDP growth, the estimated beta for that sector needs to be observed as significantly different from zero.

In Model 2, we add control variables, all chosen for their significant relationship with GDP growth detected in previous research.[17] This is done in order to verify whether the corporate bond spreads have predictive power even beyond what can be detected in the control variables. The results from Model 1 and 2 will be evaluated based on their goodness-of-fit (the adjusted R-squared) and the significance levels of the relevant coefficients.[18]

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[15] In our simple GDP model, $y_{t,t+k}$ is regressed against lagged values of itself in the "plain" AR(p) model $y_{t,t+k} = \alpha + \sum_{i=1}^{p} y_{t-i,t+k} + \varepsilon_t$.

[16] See *Appendix B* for an overview of the different lag lengths used in the different regressions.

[17] For further information on the sector spreads and the control variables, see section *4.2 The Data Set.*

[18] The adjusted R-squared measures the regression's goodness-of-fit, and by taking the number of independent variables into account the measure can be compared across regressions. Adjusted R-squared is calculated as $\bar{R}^2 = 1 - \frac{\sum \hat{u}_t^2/(n-m)}{\sum y_t^2/(n-1)}$, where n is the number of observations and m is the number of parameters in the model.

3.2 Out-of-Sample Forecasting

In our out-of-sample analysis, we will examine how well the corporate bond spreads predict future values of GDP growth. We use Model 1 and 2 and the estimates from the in-sample period in order to predict GDP growth in our out-of-sample period.

The predictions will be evaluated based on their Root Mean Square Error (hereinafter RMSE), which is calculated as

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_{t,t+k} - y_{t,t+k})^2},$$

where $\hat{y}_{t,t+k}$ is the estimated value of GDP growth. The RMSE summaries the distance between the forecasted and the realised value at each point in time and hence, the regression with the lowest RMSE will be the one preferred for forecasting purposes.

3.3 Econometric Issues

Following the discussion by Harri and Brorsen (2009), our model specification will generate overlapping data as we use quarterly observations but change in GDP for horizons longer that a quarter. For example, looking at the two-quarter horizon, we have one observation of change in GDP between Q1 and Q3 1999 followed by an observation of change in GDP between Q2 and Q4 the same year. As a result, the GDP change between Q2 and Q3 is accounted for twice.

The reason for calculating GDP growth using equation (3), and thereby generating overlapping data, is to achieve a higher number of observations. However, it will give our sample a moving-average error term, i.e. autocorrelation in the error term.[19] This is one of the main econometric issues when using this type of annualized-growth specifications, first discussed by Hansen and Hodrick (1980). They showed that the data series will generate inefficient estimates and that the hypothesis testing of beta being different from zero will become biased. In order to adjust for the generated nonstandard t-statistics, we will use the Newey and West (1986) corrected standard errors, which also adjust for heteroscedasticity.[20]

[19] Note that this is not the estimated error term but the white-noise stochastic error term, i.e. the error term satisfying all assumptions of a random stochastic process.

[20] Heteroscedasticity refers to the error term being correlated with the independent variable, for further information see Gujarati (2003) and Wooldridge (2009).

Another common problem when dealing with time series is the potential occurrence of structural breaks. A structural break, such as new regulation or extensive changes in the business cycle, could lead to difficulties in interpreting regression results as it often makes the model unstable over time. To avoid such issues and reduce the noise in our estimates, we exclude the recent financial and economic crisis from our initial sample period. After conducting our in- and out-of sample analyses, we will however extend our sample period to include the crisis. Doing so, we will investigate how our model handles a structural break.

4. Data Descriptions and Adjustments

This section aims at describing the division of our sample periods, the variables employed and the data adjustment necessary for conducting our analysis. A summary of the variables and their form in our regressions can be found in *Appendix C*.

4.1 The Sample Period

The sample period of our analysis is restricted by the existence of the euro market, which reaches from 1999Q1 to present day.[21] As discussed, we will remove the recent financial and economic crisis from our sample to avoid the problem of structural breaks. We choose to end the sample period when the recession starts. As a recession is generally identified as two consecutive quarters of negative GDP growth, the last quarter will be 2008Q1. As we wish to conduct both an in-sample and an out-of-sample analysis, we have also split our sample period into two. To get the same number of forecasted observations at each horizon of GDP growth, the break between the in- and out-of sample periods will differ. The exact dates of each period are defined in *Table 4.1*.

Table 4.1: Division of Sample Period (excluding financial crisis)

Dependent variable	$y_{(t, t+1)}$	$y_{(t, t+2)}$	$y_{(t, t+3)}$	$y_{(t, t+4)}$
In-sample period	1999Q1-2007Q1	1999Q1-2006Q4	1999Q1-2006Q3	1999Q1-2006Q2
Out-of-sample period	2007Q2-2008Q1	2007Q1-2007Q4	2006Q4-2007Q3	2006Q3-2007Q2

When extending our sample period to test the predictive power of our models over a structural break, the in- and out-of sample periods will be redefined according to *Table 4.2*.

Table 4.2: Division of Extended Sample Period (including financial crisis)

Dependent variable	$y_{(t, t+1)}$	$y_{(t, t+2)}$	$y_{(t, t+3)}$	$y_{(t, t+4)}$
In-sample period	1999Q1-2008Q1	1999Q1-2007Q4	1999Q1-2007Q3	1999Q1-2007Q2
Out-of-sample period	2008Q2-2009Q3	2008Q1-2009Q2	2007Q4-2009Q1	2007Q3-2008Q4

We will study the relationship between GDP growth and sector corporate bond spreads at horizons ranging from one to four quarters. As presented in section *2.2 Previous Research*, most findings

[21] The euro was introduced as an accounting currency on 1 January 1999 and as cash three years later, on 1 January 2002.

indicate that the leading properties should be found within this time frame. Also, restricting the analysis to four quarters gives our work reasonable delimitation.

In the next section, the sample periods will also be illustrated graphically together with the evolution of the corporate bond spreads and GDP.

4.2 The Data Set

Data series on euro area GDP are collected from the European Commission's statistical database Eurostat and is adjusted for inflation, seasonality, and calendar effects.[22] The seasonal adjustment removes the effect of seasonal patterns while the working-day correction takes the different number of working days in each quarter into account. Both of these patterns can affect the growth rate significantly when looking at quarterly horizons. The series is adjusted for inflation by stating prices with reference year 2000.

We define the corporate bond spread, i.e. our proxy for the EFP, as the difference between the yield on a corporate bond and a benchmark interest rate with the same maturity. Following a discussion in Fabozzi (2010), we have chosen to use the euro swap curve as the benchmark in our calculations. Compared to government bonds, he brings forward that the swap rate can be a more representative benchmark as the government bond market face technical and regulatory factors not present in other securities markets.[23] The euro swap rate is collected with help from Nordea and their e-markets database.

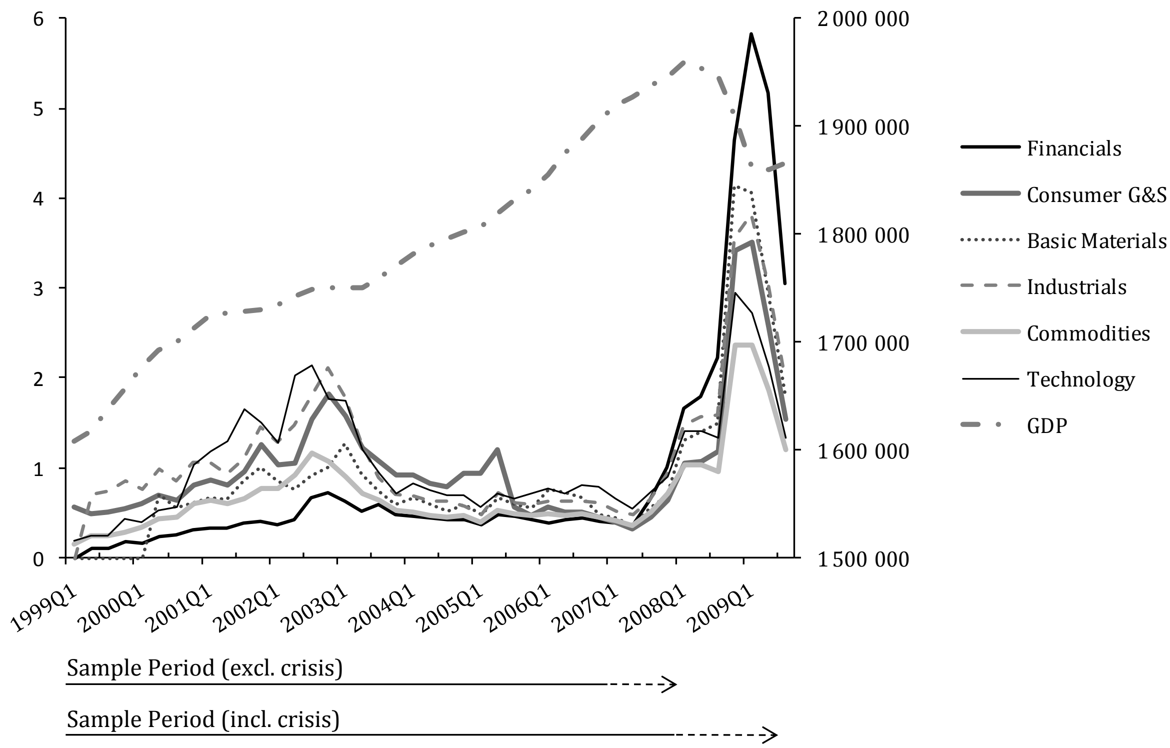
Corporate bond yields are taken from Markit iBoxx EUR Benchmark Indices. These consist of investment grade corporate bonds issued in euro, divided into six sectors covering Financials, Consumer Goods & Services, Basic Materials, Industrials, Commodities and Technology as well as an overall index including all sectors. The sectors are chosen to cover the whole spectrum of corporate bonds and should be different enough for our models to detect sector-specific patterns. We use indices from Markit as it is a leading fixed-income index provider with indices widely used as

[22] Series are based on a changing composition, currently includes Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain.

[23] Government bonds face specific tax rules which affect their yield curve. Also, there are only a small number of maturities issued which means that a synthetic yield curve must be created through bootstrapping. Such a yield curve may not be representative of real interest rates at every given maturity point. In the swap market, there is no rigid regulation and there is a wide range of maturities available. Even though the swap rate includes liquidity and credit risk, it is seen as representing true interest rates. Many countries today prefer to use the swap curve as their benchmark interest rate rather than their government bond curve. For further discussion, see Fabozzi (2010).

benchmarks by investors and asset managers.[24] As De Bondt (2002) and Buchmann (2009) find investment-graded bonds to contain the most predictive power, the index also suits the specific purpose of our work. As the aim of an index is to symbolise the developments in a wider market, the use of a bond yield index should give the sector indices representativeness even though the number of bonds in some sectors is relatively small. A graphical overview of the evolution of the sector spreads and GDP during the different sample periods is illustrated in *Graph 4.1*

Graph 4.1: Evolution of Corporate Bond Spreads and GDP 1999Q1-2009Q3



Corporate bond spreads are represented on the left axis in percentage points. GDP is represented on the right axis in millions or euro (adjusted for seasonality, calendar effects and inflation, reference year 2000).

The graph shows that in 2008 and 2009, the patterns of GDP and the sector corporate bond spreads are clearly different than in earlier years. As the euro-area market is relatively young, two years of extreme values implies a structural break. This validates our decision of excluding the recent crisis from our initial sample period but also enables us to test how our results change when extending the sample period to include a structural break. The two sample periods are illustrated by the

[24] The indices are calculated using prices from several leading investment banks, ensuring high quality pricing. Rebalancing is done monthly and weights are based on market capitalization. For more information, visit the Markit iBoxx webpage.

arrows below the graph, where the continuous part of the arrow denotes the in-sample period and the dotted part denotes the out-of sample (forecasting) period. Studying the evolution of the different sector spreads, they seem to follow the same path over time. Even so, the variety in level between the different spreads is noteworthy, providing an additional motive for searching for predictive content at the sector level.

We have elected our control variables on the basis of their evident relationship with GDP growth noted in previous research. The variables chosen are inflation in the euro area, the euro swap term spread, and US GDP. We include inflation as Fisher (1993) and Mueller (2009) find it to be negatively correlated with future GDP growth. The inflation measure we implement is the "Harmonised Index of Consumer Prices" (HICP), which is the measure the European central bank uses when deciding on their main interest rate.[25] The term spread is included as it in the past has been a good indicator of future economic activity, studied by for example Estrella and Hardouvelis (1991). Even though this relationship has lost its significance in recent years, we include it to be certain that any potential predictive content in the corporate bond spread does not stem from the term spread. Finally, we follow Espinoza, Fornari, and Lombardi (2009) and include US GDP growth as the US business cycle tends to lead the European by a couple of quarters. Both inflation and the US GDP are collected from the Nordea e-markets database.

When deciding what data set to include, it is important to search for data series that are representative for the purpose of the analysis. In our case, we need corporate bond spreads that are representative of the EFP in the euro area to be able to validate the usage of euro area GDP. The bond index we use to calculate our spreads consists of corporate bonds denominated in euro, and although the majority of the issuers are euro-area residents, some are not. The discrepancy this may cause between the origin of our corporate bond spreads and GDP is impossible to define in quantitative terms. As GDP measures production according to location and not firm ownership, we cannot reject the idea that non-euro area firms issuing in euro still contribute to the euro area GDP through local presence.[26] Together with the fact that the index in question is a widely accepted benchmark for the euro area market, we believe this validates the use of our corporate bond spreads as good proxies for the EFP in the euro area.

[25] For more information regarding inflation in the euro area, visit the European Central Bank webpage.
[26] The measure of GDP can be compared to other measures such as GNI (Gross National Income) which focuses on production ownership rather than location. More details can be found in most macroeconomics books, for example Mankiw (2003).

4.3 Data-Set Adjustments

GDP is observed with quarterly frequency and we therefore use quarterly data in our analysis. As corporate bond spreads and the euro swap rate is observed daily, we follow Estrella and Hardouvelis (1991) and Buchmann (2009) and adjust the data series to quarterly by taking period averages.[27]

When using time-series data in regression analysis, it is important that the data is stationary, i.e. that its joint distribution is constant over time. Before running our regressions, we therefore perform a Dickey-Fuller test of unit root on each variable. The results show that our independent and control variables all are non-stationary. To solve for the problem of a unit root, the variables need to be first differenced.[28] First differencing also ensures that our variables are weakly dependent, which is the time-series version of the random-sampling requirement. For the in-detail test results and a further discussion regarding the problem of non-stationarity, see *Appendix D*.

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[27] Other authors such as Stock and Watson (2003) have used spot time data at the end of each quarter. We argue however that period averages are more representative as it avoids daily irregularities.

[28] We will thereby look at changes in corporate bond spreads rather than their levels. This was also motivated by Chan-Lau and Ivaschenko (2001) who argued that it thus should give an indication of the direction of change in the credit quality, which then should foresee changes in real GDP.

5. Results

In this section we present the results of our regression models, divided into in- and out-of-sample generated results. The section ends with the results from testing the models' accuracy over structural breaks. A detailed overview of all obtained results can be found in *Appendix E*.

5.1 In-Sample Regression Analysis

Our in-sample regression analysis aims to examine the existence of the financial accelerator at a sector level. However, we start off by confirming the more general relationship found by De Bondt (2002) and Buchmann (2009), who both argue that investment-grade corporate bond spreads in the euro area contain information of future real activity, a conclusion we base on the results from regressing the corporate bond spread containing all sectors against GDP growth. The all-sector regression estimates are shown to be significant and improves adjusted R-squared in both Model 1 and Model 2 compared to levels generated in the simple GDP model. The results are summarised in *Table 5.1*, *Table 5.2* and *Table 5.3*. Looking at the theory of the financial accelerator, the results validates our spread calculation, and shows it to be a good proxy of the EFP. The relationship can be detected on a one-, two-, and three-quarter horizon, but later it seems to disappear, a trend seen throughout our results. These horizons are very much in line with the findings of De Bondt (2002) and Mueller (2009) who find indications of predictive power up to ten months into the future in the euro area and the US respectively.

Table 5.1: In-Sample Regression Results Simple GDP Model

GDP Growth	k=1	k=2	k=3	k=4
$\bar{R}^2$	0,2784	0,7060	0,7605	0,8741
F sig.	0,0005	0,0000	0,0000	0,0000

Turning to our sector-specific spreads, regression results using Model 1 show that significant relationships are evident within all sectors, except Financials, at one or several horizons. The main results from Model 1 are summarised in *Table 5.2*. Consumer Goods & Services and Industrials show the strongest relation to real activity, both being significant at several horizons. As expected, all significant spreads have negative coefficients, confirming that rising corporate bond spreads contribute to falling GDP growth in the future.

Table 5.2: In-Sample Regression Results Model 1

k		Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
1	$\hat{\beta}$	-2,1671*	-2,2562	-1,0578	-2,2758*	-1,3022**	-1,2673	-0,6340
	$\bar{R}^2$	0,4573	0,4405	0,4523	0,3870	0,5132	0,4433	0,4381
2	$\hat{\beta}$	-1,9011**	-1,6885	-1,1179***	-0,7918	-1,3400***	-2,4336**	-0,8962**
	$\bar{R}^2$	0,7591	0,7401	0,7670	0,6388	0,7416	0,7634	0,7598
3	$\hat{\beta}$	-1,7701**	-0,7538	-0,3719*	0,1046	-0,1410	-1,2400	-0,4929*
	$\bar{R}^2$	0,8369	0,8800	0,8860	0,8721	0,8782	0,8874	0,8880
4	$\hat{\beta}$	-0,3302	-0,0763	0,0038	0,0933	-0,2188	-0,6802	-0,3041
	$\bar{R}^2$	0,8951	0,8965	0,8965	0,8651	0,8872	0,9002	0,9014

The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level.

In Model 2, we add our control variables inflation, the term spread, and US GDP. A summary of the results is provided in *Table 5.3*. Apart from a slight fall in adjusted R-squared, the majority of the significant relationships found using Model 1 remains. The control variables are all insignificant, either implying that our sector spreads are better at predicting future real activity, or that our choice of control variables could have been improved. Since, we base the selection on findings in previous research we argue that their insignificance implies that corporate bond spreads do contain more predictive information about future GDP growth than do US GDP, inflation, and the term spread.

Table 5.3: In-Sample Regression Results Model 2

k		Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
1	$\hat{\beta}$	-2,2014*	-2,5300	-1,0857	-1,4223	-1,2616*	-1,2992	-0,6438
	$\bar{R}^2$	0,3955	0,3785	0,3909	0,4594	0,4735	0,3689	0,3733
2	$\hat{\beta}$	-1,8646**	-1,7819	-1,1356***	-0,4464	-1,300**	-2,4626**	-0,9095**
	$\bar{R}^2$	0,7302	0,7113	0,7420	0,6394	0,7137	0,7378	0,7316
3	$\hat{\beta}$	-1,64447**	-0,7825	-0,3633*	0,1401	-0,5810	-1,2473	-0,5373
	$\bar{R}^2$	0,8320	0,8645	0,8644	0,8485	0,8103	0,8730	0,8744
4	$\hat{\beta}$	-0,2417	-0,3303	-0,0419	0,1403	-0,2558	-0,7034	-0,1606
	$\bar{R}^2$	0,8968	0,8966	0,8961	0,8820	0,8976	0,9005	0,8974

The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level.

The number of lagged dependent variables included varies between our regressions in accordance with the Akaike Information Criterion, further information can be found in *Appendix B*. Most commonly, one or two lags are added and these have significant coefficients in all regressions. Our results indicate that, even after controlling for lagged values of GDP growth, all our sector spreads but Financials contain predictive power over future GDP growth and could thus be useful for predictive purposes.

All in all, the two sectors particularly noteworthy in our in-sample regression results are Consumer Goods & Services and Industrials, both being highly significant in detecting GDP change two quarters ahead and both contributing to high adjusted R-squared levels compared to the simple GDP model. Overall, the highest significance levels are found at the two-quarter horizon, suggesting that this may be the time it takes for the financial accelerator to work. From our in-sample analysis we thereby conclude that we see strong indications of sector spreads containing predictive power over future GDP growth. In other words, we confirm that a financial accelerator is detectable at a sector level.

5.2 Out-of-Sample Forecasting

In our out-of-sample analysis, we investigate which sector corporate bond spread at each forecast horizon can provide the most accurately predicted values for GDP growth, using our in-sample estimates. As described in section *3. Methodology*, the evaluation of the different regressions will be based on their levels of Root Mean Squared Error (RMSE). The results are presented in *Table 5.4* and *Table 5.5.*

Although the in-sample regression analysis gives obvious indication of predictive power, the actual forecasting results are not as straight forward. The sector regression providing the lowest RMSE, i.e. the highest forecasting accuracy, varies depending on the horizon of GDP growth. Using Model 1, the sector spread based on Industrials provides the best predictive power. However, at that horizon, only the lagged values of GDP growth are significant. Thus, when predicting GDP growth a year ahead, the forecasting power resides in the lagged values of GDP growth itself. Studying the two-quarter horizon, where our in-sample analysis shows corporate bond spreads to have the strongest explanatory power, we find relatively low RMSE values. Again the best predictor belongs to the Industrials spread, and at this horizon the spread is highly significant.

Table 5.4: RMSE Out-of-Sample Forecasting Model 1

	Corporate all	Financials	Consumer G&S	Basic Material	Industrials	Commodities	Technology
k=1	1,79780*	1,72749	2,02904	(1,51633*)	1,92156**	2,06134	2,07783
k=2	0,57550**	0,57398	0,63751***	0,66695	(0,55747***)	0,57908**	0,67531**
k=3	(0,56084**)	0,75387	0,91113*	0,98388	0,95003	0,74127	0,78576*
k=4	0,48648	0,48782	0,48752	0,48641	(0,47551)	0,48943	0,48605

Values in parenthesis indicate the lowest RMSE at each horizon. The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level.

In Model 2, the all-sector corporate bond spread shows the lowest RMSE, suggesting that forecasting using sector-level information may be inferior to using the whole spectrum of sectors. But again, the results are highly dependent on the horizon of interest. If we look two quarters ahead, the spread for Industrials again generates the highest forecasting accuracy.

Table 5.5: RMSE Out-of-Sample Forecasting Model 2

	Corporate all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	1,78815*	1,65845	2,05963	(1,39294)	1,8494*	2,07855	2,07198
k=2	0,61227**	0,62993	0,72483***	0,67277	(0,52485**)	0,64743**	0,66824**
k=3	(0,48398**)	0,75998	0,92433*	1,03358	0,52881	0,74434	0,72960
k=4	0,59567	0,61107	0,60074	0,57995	0,59688	0,59363	(0,57811)

Values in parenthesis indicate the lowest RMSE at each horizon. The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level.

5.3 Model Accuracy with Structural Break

When extending our sample-period, significance levels of the corporate bond spreads rise almost unanimously, suggesting that the financial accelerator is even more evident in times of turmoil. Significance levels and RMSE can be found in *Table 5.6* and *Table 5.7*. The spread of Financials, which previously was insignificant across the boarder, is now highly significant on the one-, two and three-quarter horizons in Model 1 and at the one- and three- quarter horizons in Model 2.[29] However, adjusted R-squared levels fall and when trying to forecast GDP growth during the out-of-sample period, now characterized by a financial and economic crisis, there is a noteworthy fall in accuracy. In both Model 1 and 2, the lowest RMSE can be found on the fourth-quarter horizon, where none of the spreads are significant.

[29] Following the results from the Dickey-Fuller tests in *Appendix D,* there is a possibility of the spread for Financials being non-stationary. Using OLS regressions, this could lead to estimation errors. For reasons discussed in *Appendix D*, we interpret the risk of non-stationarity in our sample to be sufficiently small.

Table 5.6: RMSE Out-of-Sample Forecasting Model 1 (including financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	4,8414**	6,0471**	(4,0049*)	4,3649***	4,1676**	4,1638	4,0909*
k=2	3,9408***	4,2825***	3,2196***	(2,8477)	3,1713***	3,5160***	3,0653
k=3	2,5491**	3,3392**	2,0248**	(1,7547)	1,8854	2,4988**	1,9742***
k=4	1,3790	(1,3163)	1,4522	2,1219	1,3247	1,3247	1,4856

Values in parenthesis indicate the lowest RMSE at each horizon. The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level.

Table 5.7: RMSE Out-of-Sample Forecasting Model 2 (including financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	5,5395***	8,0972***	(4,0779)	4,5704**	4,3850**	4,3461	4,4675*
k=2	3,6950**	3,7196	2,9575***	(2,4377)	3,2877***	3,9010**	3,2350*
k=3	2,3355**	2,8500**	1,7726**	(1,5645)	1,6357	2,1120***	1,6815**
k=4	1,3790	1,3526	(1,3443)	1,6174	1,3546	1,3930	1,6178

Values in parenthesis indicate the lowest RMSE at each horizon. The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level.

6. Discussion

In this paper, we study the relationship between the credit market and real activity based on the theory of the financial accelerator. Finding a link between financial markets and economic cycles is a popular area of research as such links could improve the ability to analyse and forecast future economic developments. The credit market and corporate bonds are especially interesting as they give us an indication of the financial health of the business community. As the financial strength is represented by the external finance premium (EFP), and spreads on corporate bonds can be seen as a proxy for the EFP, these spreads can contain information about the future state of the economy. Previous studies, although disagreeing on which type of corporate bond spread and causality model to use, conclude that the spreads do have a significant relationship with economic variables, stemming from the financial accelerator and the EFP. As previous research has focused on categorising spreads according to bond maturity and credit rating, we wish to add to the in-debt analysis of the causal relationship by analysing corporate bond spreads on a sector level. If some sectors contribute to the causal relationship more than others, then forecasting models including corporate bond spreads could be improved by excluding those sectors lacking predictive power.

To summarize our findings, there is a relationship between corporate bond spreads and future GDP growth on a sector level, confirming the presence of a financial accelerator. In particular, the spreads for Consumer Goods & Services and Industrials can detect changes in GDP growths two quarters ahead with high significance. Also, sector-specific information is shown to be useful for forecasting purposes. The results are however heavily dependent on the forecast horizon. If forecasting GDP growth three-quarters ahead, sector-specific spreads are inferior to the general corporate bond spread, but on the two-quarter horizon, the sector spread for Industrials help generate the highest forecasting accuracy. Depending on the purpose of forecasting, the horizon of interest most certainly differs between market participants and finding a variable that contains forecasting power is thus not enough, it must also be forecasting at the right horizon. This contributes to previous research which, to our knowledge, has not yet studied the financial accelerator at the sector level or used sector information to forecast real activity.

To create a forecasting model as stable as possible, we wanted to avoid structural breaks in our analysis. We thus excluded the financial crisis from our sample period in the hopes of reducing noise, which seems to give us satisfying results. To test the validity of our results, we however decided to run our models again, this time including the financial crisis. This results in increased levels of significance across all sectors and horizons. One of the most interesting changes is that after being insignificant across the boarder, the coefficient of Financials is now highly significant at forecasting horizons of one to three quarters ahead. The extended in-sample period now ends in 2008Q1, i.e. at a time when market turmoil was on the rise, but still before the development turned into a wide-spread crisis. This implies that the predictive power of Financials increased right before the financial crisis culminated. This may suggest that what we should be looking for is not significant relationships per se, but how these relationships seem to change over time. Searching for relationships that are stable over time may thus not give us the whole story. As Stock and Watson (2003) argue that the relationship found between corporate bond spreads and real economic activity is not stable over time, analysing the actual changes might be an additional source of useful information.

When including the crisis, the levels of significance rise for all our sector spreads, indicating that the effect of the financial accelerator increases in volatile times, results that are in line with those found by Mueller (2009) and Gilchrist, Yankov, and Zakrajsek (2009). This is consistent with the theory which states that small events, through affecting financial-market frictions, in other words the EFP, can escalate into large business-cycle swings. The adjusted R-squared levels are however lower than when using the original sample period. This indicates that, even though the significance of the spreads rises, there is something else affecting GDP growth in turbulent times that is not reflected in the spreads, control variables, or lagged GDP growth. Studying the RMSE values from the out-of-sample analysis shows that forecasting accuracy falls markedly when trying to forecast GDP growth during the crisis. Including a structural break thus both improves and aggravates the quality of using sector spreads. One the one hand, the presence of a financial accelerator at the sector level seems even more evident than before, but on the other hand, the forecasting accuracy falls. Our results are thus not stable over a structural break, and as for many economists in the past, our model might not be stable over time.

To our knowledge, our analysis is the first studying the relationship between corporate bond spreads and real economic activity at the sector level and the results can thus neither be confirmed nor contradicted by previous results. The findings presented are therefore heavily dependent on the assumptions made, such as our choice of benchmark interest rate and bond-yield index. As our findings indicate that forecasting could be improved using sector, rather than overall, corporate bond spreads, the research area should gain from further investigation. One drawback of our analysis is the relatively short sample period available in the euro area. Even though De Bondt, already back in 2002, found the market to be integrated enough to contain useful information, longer sample periods are motivated to properly analyze the relationships and how they change over time. Studying more mature geographical markets, such as the one for dollar-denominated corporate bonds, could hence yield useful insight. Regardless the market of choice, using other benchmarks and bond yields to calculate spreads could also add to the analysis of sector-specific bond spreads and hopefully give our findings additional support.

A final note relates to our focus on analysing the existence of specific causal relationships. Our results show that the financial accelerator does exist at the sector level and that such relationships can be of valuable use for forecasting. However, we provide no theory of why some sectors are better at forecasting real economic activity than other. To further assist in interpreting the linkages between the corporate bond spreads and real activity, a natural next step is to investigate the actual sources of the predictive content in the different sectors. As noted by for example Gertler and Lown (2000) and Stock and Watson (2003), one financial variable alone will not yield a perfect forecast but to develop useful models, the predictive nature of each variable employed must be carefully analyzed. As the insights gained in this paper increases the knowledge of the corporate bond spread as a predictive variable it should thus also benefit the general search for the perfect forecasting model.

7. Conclusion

Searching financial variables for predictive power over real economic activity has been a popular research field in the past few decades. Recently, several studies have found that corporate bond spreads seem to be good predictors of real activity, a relationship validated by the theory of the financial accelerator. However, the literature has so far not considered other bond classifications than credit rating and maturity when searching for predictive power. To fill this gap, our aim was to study whether the financial accelerator can be detected at the sector level and also if some sectors are better predictors of future GDP growth than others. By removing sectors with inferior predictive ability, the forecasting accuracy of models using corporate bond spread could be improved.

To avoid structural breaks, we first excluded the recent financial crisis from the sample period. Our regression results confirmed the existence of a financial accelerator at the sector level for all sectors but Financials, and also that sector specific spreads can add to the forecasting accuracy even beyond lagged values of GDP and our controls. The results however varied with the forecasting horizon. While the highest forecasting accuracy was found at the three-quarter horizon, generated by the all-sector corporate bond spread, someone interested in GDP growth two quarters into the future would have received more precise estimates using the sector spread for Industrials.

Including the financial crisis to test the stability of our model suggested that the financial accelerator is even more evident in times of turbulence. The significance of all sector spreads, including Financials, rose notably. However, the forecasting accuracy fell.

The noteworthy change in the spread for Financials, going from insignificant to highly significant right before the financial crisis hit the wide market, lead us to suggest that rather than searching for stable relationships, maybe we should shift our attention to studying how these relationships change over time.

Our analysis showed that there are benefits from looking at sector-specific information, but that the relationships are highly dependent on the horizon of GDP growth. These findings motivate further research at the sector level, using both other geographical markets and different spread calculations to further improve our understanding of the workings of the financial accelerator.

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Appendix A. Credit Ratings

Table A.1: Credit Ratings Defined by Standard & Poor's

Credit Quality	Credit Rating
Investment Grade	
Highest credit quality, extremely strong capacity to meet financial commitments.	AAA
High credit quality, very strong capacity to meet financial commitments.	AA+ to AA-
Strong capacity to meet financial commitments.	A+ to A-
Adequate capacity to meet financial commitments.	BBB+ to BBB-
Speculative Grade / High Yield	
Ongoing uncertainty can lead to inadequate capacity to meet financial commitments.	BB+ to BB-
Ongoing uncertainty likely to lead to inadequate capacity or willingness to meet financial commitments.	B+ to B-
Current vulnerability, not likely to meet financial commitments in case of adverse events.	CCC+ to CCC-
Current high vulnerability to nonpayment, default is likely.	CC
Current high vulnerability, default is imminent.	C
Payments not made on date due, in default.	D, SD

Source: Standard & Poor's Ratings Definitions, Global Credit Portal.

Appendix B. The Akaike Information Criterion

Table B.1: Optimal Number of Lags in Model 1 and 2 (excluding financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	1 (1)	1 (1)	1 (1)	1 (1)	1 (1)	1 (1)	1 (1)
k=2	2 (2)	2 (2)	2 (2)	2 (2)	1 (1)	2 (2)	2 (2)
k=3	1 (1)	2 (2)	6 (6)	6 (6)	6 (1)	2 (2)	2 (2)
k=4	2 (2)	2 (2)	2 (2)	2 (2)	2 (2)	2 (2)	2 (2)

Numbers represent the optimal number of lags according to the Akaike Information Criterion for the dependent variable in the in-sample regressions using Model 1 (first number) and Model 2 (number in parenthesis).

Table B.2: Optimal Number of Lags in Model 1 and 2 (including financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	1 (3)	1 (1)	1 (1)	1 (3)	1 (1)	1 (1)	1 (1)
k=2	6 (8)	3 (9)	6 (8)	6 (8)	8 (8)	7 (8)	7 (8)
k=3	5 (6)	6 (6)	6 (6)	5 (6)	6 (6)	5 (6)	5 (6)
k=4	6 (6)	6 (6)	2 (6)	10 (6)	6 (6)	6 (6)	2 (3)

Numbers represent the optimal number of lags according to the Akaike Information Criterion for the dependent variable in the in-sample regressions using Model 1 (first number) and Model 2 (number in parenthesis).

Table B.3: Optimal Number of Lags in Simple GDP Model

	k=1	k=2	k=3	k=4
Lags	1	2	6	2

Numbers represent the optimal number of lags according to the Akaike Information Criterion for the dependent variable in the simple GDP model where the dependent variable is regressed only on lagged values of itself.

Table B.4: Optimal Number of Lags in Dickey-Fuller Test

	GDP	Corporates all	Financials	Consumer G&S	Basic Materials
level	-	2	9	2	2
1st diff	1	2	8	2	0

Industrials	Commodities	Technology	Inflation	Term Spread	US GDP
2	2	1	5	10	1
2	0	0	4	3	0

Numbers represent the optimal number of lags according to the Akaike Information Criterion when testing for unit root using Dickey-Fuller.

Appendix C. The Data Set

Table C.1: Overview of the Data Set

Variable	Description		Form in regression	Source
Real GDP	Euro area GDP, quarterly data, adjusted for inflation, seasonality and calendar effects.		Natural logarithm	Eurostat
Corporate Bond Spreads	Calculated as the difference between bond yield and benchmark interest rate. Daily bond yields taken from Markit iBoxx EUR Benchmark Index containing investment grade corporate bonds issued in euro, divided into sub-sectors. Converted into quarterly by taking period averages. Euro Swap rate used as benchmark interest rate, interpolated to match bond maturities. Bonds divided into sub-sectors Financials, Consumer Goods & Services, Basic Materials, Industrials, Commodities and Technology. (Number of bonds per sub-sector as of April 8, 2010.)	- *Financials*, containing sub-indices Banks, Financial Services and Insurance. (546 bonds) - *Consumer Goods & Services*, containing sub-indices Media, Retail, Automobiles, Food & Beverage, Personal & Household Goods and Travel & Leisure. (168 bonds) - *Basic Materials*, containing sub-indices Basic Resources and Chemicals. (54 bonds) - *Industrials*, containing sub-indices Construction & Materials and Industrial Goods & Services. (110 bonds) - *Commodities*, containing sub-indices Oil & Gas and Utilities. (221 bonds) - *Technology*, containing sub-indices Telecommunications and Technology. (117 bonds)	First difference	Markit iBoxx EUR Benchmark Index
Term Spread	Calculated as the difference between the 1 and 10 year euro swap rate.		First difference	Nordea e-markets
Inflation	Harmonized Index of Consumer Prices, HICP, quarterly data.		First difference	Nordea e-markets
US GDP	United States GDP, quarterly data, adjusted for inflation and seasonality.		First difference	Nordea e-markets

Appendix D. Dickey-Fuller Test of Unit Root

To estimate a model which can be used for analysing time-series data, the features of the model have to be constant over time. Therefore the data is required to be stationary. Gujarati (2003) defines a data series as stationary if its mean and variance are constant over time, and if the value of the covariance between two time periods depends only on the distance and not on the actual time for which the covariance is computed. As a first step in testing for stationarity, we analyse our variables graphically to look for possible trends or obvious unit roots. The graphs are included at the end of this appendix. None of the variables contain an observable trend, but to confirm, we use the widely accepted Dickey-Fuller test.

If the data is not stationary we will get a so called unit root process, which can be expressed as $\rho = 1$ in equation

$$Y_t = \rho Y_{t-1} + u_t, \qquad where -1 \leq \rho \leq 1,$$

when $\rho = 1$, the series contains a unit root since Y_t depends fully on its last past value and hence is non-stationary.[30] The test is conducted by first subtracting Y_{t-1} on both sides to generate equation

$$\Delta Y_t = Y_t - Y_{t-1} = \delta Y_{t-1} + u_t, \qquad where\ \delta = (\rho - 1).$$

The null hypothesis we wish to reject is then $\delta = 0$.

When autocorrelation is present in the error terms, as in our model, an adjusted version of the test must be applied, called the Augmented Dickey-Fuller test (ADF). This version includes lagged values of the variable in question and together with a more general assumption of a non-zero mean, we arrive at the test equation

$$\Delta Y_t = \alpha_1 + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i Y_{t-i} + \varepsilon_t, \qquad where\ \delta = (\rho - 1),$$

where α_1 is an intercept reflecting that the series' mean is not zero, and where the number of lags of Y is chosen by applying the Akaike Information Criterion.[31] We still want to reject the null hypothesis that the series contain a unit root.

H_0: $\delta = 0$ *(the series is non-stationary)*

H_1: $\delta < 0$ *(the series is stationary)*

H_0 is rejected if the observed t-statistic is lower than the critical t-value, a value that change with the number of observations in the series. For our sample, the critical value lies around -2,4 on a 15-percent significance level.

The results from running ADF for all variables are presented in *Table D.1*. As one can observe, the variables were not stationary in their level form and hence had to differentiated. In its first-difference form, all independent variables were proved to be stationary except the corporate bond spread for Financials. Using the second-difference would most certainly give us stationarity, but in that form the spread would have little intuitive meaning for the purpose of our work. After studying the graphed version of the spread, we argue that the risk of a unit root is sufficiently small and we therefore choose to include it as an independent variable in its first-difference form. When

[30] Note that the terms unit root, non-stationarity and random walk can be treated as synonymous in this matter.
[31] See *Appendix B* for a specification of the number of lags.

analysing the results using Financials, one should however keep the possibility of non-stationarity in mind.

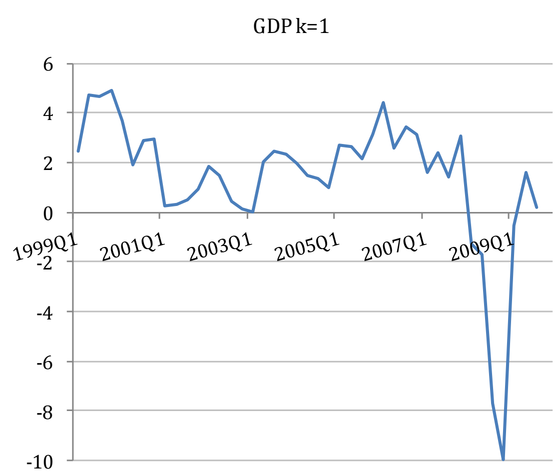
Table D.1: D-Fuller Test Results for Variables in Level and First-Differenced Form

	Level Values		First-Difference Values	
	t-value	Significance level	t-value	Significance level
GDP growth	-	-	-2,527	0,109*
Corporates All	-1,51	0,5283	-3,835	0,0026***
Financials	-0,776	0,8260	-1,965	0,3019
Consumer G&S	-1,909	0,3279	-4,127	0,0009***
Basic materials	-1,617	0,4740	-4,593	0,0001***
Industrials	-1,707	0,4277	-3,606	0,0056***
Commodities	-1,761	0,4000	-4,965	0,0000***
Technology	-2,429	0,1336	-5,473	0,0000***
Inflation	-3,547	0,0069***	-3,278	0,0159**
US GDP	-2,845	0,0521**	-2,599	0,0932*
Term Spread	-2,349	0,1566	-9,683	0,0000***

The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level.

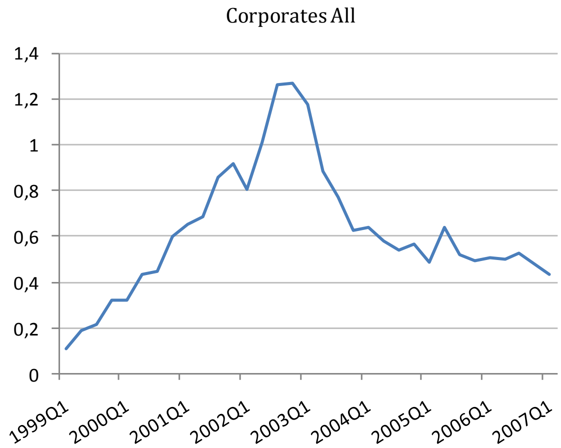
Our GDP-growth variable is by its form already presented in a type of first-difference, hence there is little econometrical as well as theoretical reason for the variable to contain a unit root. The significance level is slightly above 10 percent, but due to our relatively small number of observations, levels up to 15 percent are accepted.

Graph D.1: Evolution of GDP growth 1999Q1 – 2009Q3



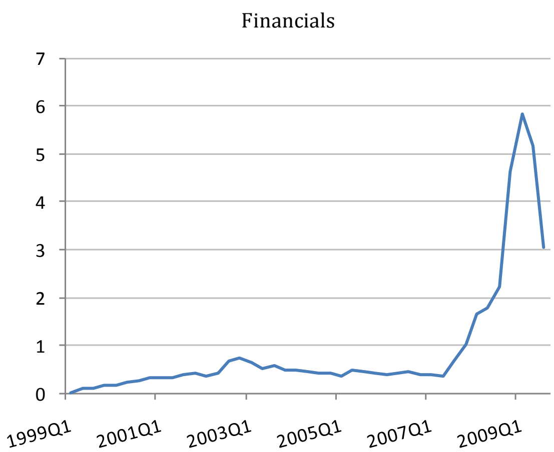
GDP growth is represented by the annualized cumulative percentage change in real GDP from time t to t+k and calculated as $y_{t,t+k} = \frac{400}{k} + \ln\left(\frac{GDP_{t+k}}{GDP_t}\right)$.

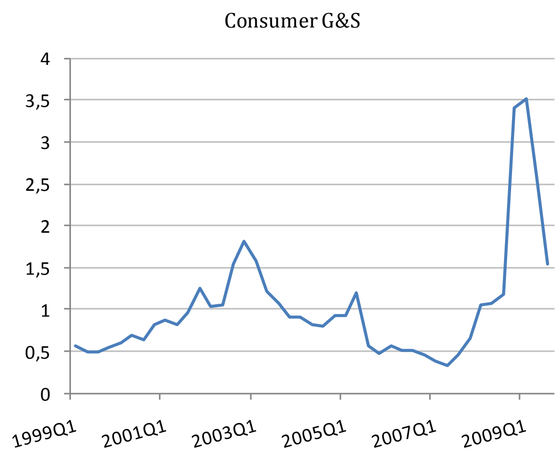
Graph D.2: Evolution of Corporate Bond Spreads (first-difference) 1999Q1 – 2009Q3



Corporate bond spreads are calculated as the difference between a bond yield index and the euro swap rate with the corresponding maturity. Spreads are graphed in first-difference form to correspond to their form used in regressions.

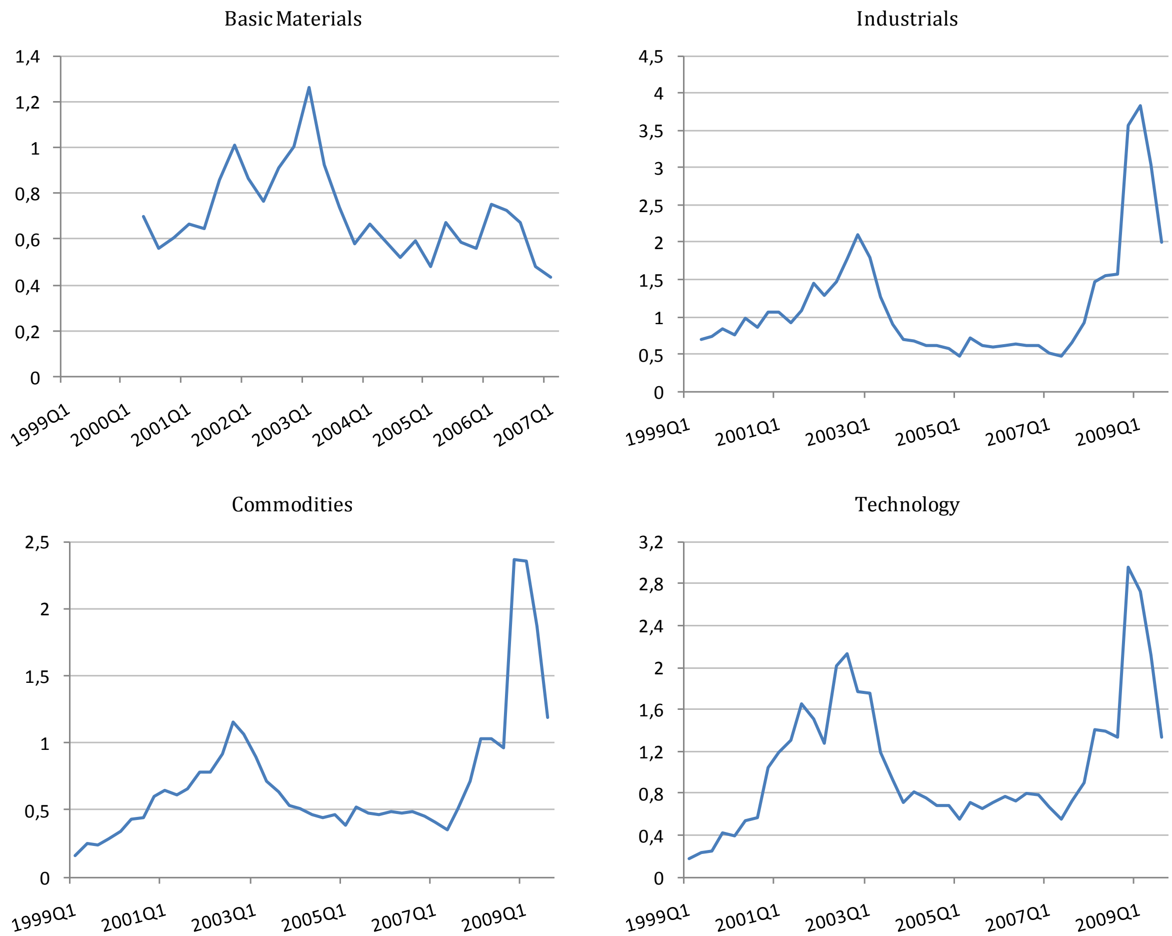
Graph D.3-4: Evolution of Sector Corporate Bond Spreads (first-difference) 1999Q1 – 2007Q1





Corporate bond spreads are calculated as the difference between a bond yield index and the euro swap rate with the corresponding maturity. Spreads are graphed in first-difference form to correspond to their form used in regressions.

Graph D.5-8: Evolution of Sector Corporate Bond Spreads (first-difference) 1999Q1 – 2007Q1



Corporate bond spreads are calculated as the difference between a bond yield index and the euro swap rate with the corresponding maturity. Spreads are graphed in first-difference form to correspond to their form used in regressions.

Appendix E. Results

Table E.1: In-Sample Regression Results Simple GDP Model

GDP Growth	k=1	k=2	k=3	k=4
$\bar{R}^2$	0,2784	0,7060	0,7605	0,8741
F sig.	0,0005	0,0000	0,0000	0,0000

Results are generated using equation $y_{t,t+k} = \alpha + \sum_{i=1}^{p} y_{t-i,t+k} + \varepsilon_t$.

Table E.2: In-Sample Regression Results Model 1 (excluding financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
GDP growth on a 1 quarter horizon							
$\hat{\beta}$	-2,1671*	-2,2562	-1,0578	-2,2758*	-1,3022**	-1,2673	-0,6340
	(1,7978)	(1,7275)	(2,0290)	(1,5163)	(1,9216)	(2,0613)	(2,0778)
$\bar{R}^2$	0,4573	0,4405	0,4523	0,3870	0,5132	0,4433	0,4381
F sig.	0,0001	0,0001	0,0001	0,0011	0,0000	0,0001	0,0001
GDP growth on a 2 quarter horizon							
$\hat{\beta}$	-1,9011**	-1,6885	-1,1179***	-0,7918	-1,3400***	-2,4336**	-0,8962**
	(0,5755)	(0,5739)	(0,6375)	(0,6669)	(0,5575)	(0,5791)	(0,6753)
$\bar{R}^2$	0,7591	0,7401	0,7670	0,6388	0,7416	0,7634	0,7598
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 3 quarter horizon							
$\hat{\beta}$	-1,7701**	-0,7538	-0,3719*	0,1046	-0,1410	-1,2400	-0,4929*
	(0,5608)	(0,7539)	(0,9111)	(0,9838)	(0,9500)	(0,7413)	(0,7878)
$\bar{R}^2$	0,8369	0,8800	0,8860	0,8721	0,8782	0,8874	0,8880
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 4 quarter horizon							
$\hat{\beta}$	-0,3302	-0,0763	0,0038	0,0933	-0,2188	-0,6802	-0,3041
	(0,4865)	(0,4878)	(0,4875)	(0,4864)	(0,4755)	(0,4894)	(0,4860)
$\bar{R}^2$	0,8951	0,8965	0,8965	0,8651	0,8872	0,9002	0,9014
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level. The values in parenthesis are the Newey and West (1986) corrected standard error of the estimates.

Table E.3: In-Sample Regression Results Model 2 (excluding financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
GDP growth on a 1 quarter horizon							
$\hat{\beta}$	-2,2014*	-2,5300	-1,0857	-1,4223	-1,2616*	-1,2992	-0,6438
	(1,7882)	(1,6585)	(2,0596)	(1,3929)	(1,8494)	(2,0785)	(2,0720)
$\bar{R}^2$	0,3955	0,3785	0,3909	0,4594	0,4735	0,3689	0,3733
F sig.	0,0023	0,0032	0,0025	0,0024	0,0006	0,0038	0,0035
GDP growth on a 2 quarter horizon							
$\hat{\beta}$	-1,8646**	-1,7819	-1,1356***	-0,4464	-1,300**	-2,4626**	-0,9095**
	(0,6123)	(0,6299)	(0,7248)	(0,6728)	(0,5248)	(0,6474)	(06682)
$\bar{R}^2$	0,7302	0,7113	0,7420	0,6394	0,7137	0,7378	0,7316
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 3 quarter horizon							
$\hat{\beta}$	-1,64447**	-0,7825	-0,3633*	0,1401	-0,5810	-1,2473	-0,5373
	(0,4840)	(0,7599)	(0,9243)	(1,0336)	(0,5288)	(0,7443)	(0,7296)
$\bar{R}^2$	0,8320	0,8645	0,8644	0,8485	0,8103	0,8730	0,8744
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 4 quarter horizon							
$\hat{\beta}$	-0,2417	-0,3303	-0,0419	0,1403	-0,2558	-0,7034	-0,1606
	(0,5957)	(0,6111)	(0,6607)	(0,5799)	(0,5969)	(0,5936)	(0,5781)
$\bar{R}^2$	0,8968	0,8966	0,8961	0,8820	0,8976	0,9005	0,8974
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level. The values in parenthesis are the Newey and West (1986) corrected standard error of the estimates.

Table E.4: RMSE Out-of-Sample Forecasting Model 1 (excluding financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	1,79780*	1,72749	2,02904	(1,51633*)	1,92156**	2,06134	2,07783
k=2	0,57550**	0,57398	0,63751***	0,66695	(0,55747***)	0,57908**	0,67531**
k=3	(0,56084**)	0,75387	0,91113*	0,98388	0,95003	0,74127	0,78576*
k=4	0,48648	0,48782	0,48752	0,48641	(0,47551)	0,48943	0,48605

Results are generated using equation $RMSE = \sqrt{1/T \sum_{t=1}^{T} (\hat{y}_{t,t+k} - y_{t,t+k})^2}$. Values in parenthesis indicate the lowest RMSE at each horizon.

Table E.5: RMSE Out-of-Sample Forecasting Model 2 (excluding financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	1,78815*	1,65845	2,05963	(1,39294)	1,8494*	2,07855	2,07198
k=2	0,61227**	0,62993	0,72483***	0,67277	(0,52485**)	0,64743**	0,66824**
k=3	(0,48398**)	0,75998	0,92433*	1,03358	0,52881	0,74434	0,72960
k=4	0,59567	0,61107	0,60074	0,57995	0,59688	0,59363	(0,57811)

Results are generated using equation $RMSE = \sqrt{1/T \sum_{t=1}^{T} (\hat{y}_{t,t+k} - y_{t,t+k})^2}$. Values in parenthesis indicate the lowest RMSE at each horizon.

Table E.6: In-Sample Regression Results Model 1 (including financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
GDP growth on a 1 quarter horizon							
$\hat{\beta}$	-3,5453**	-3,6031**	-1,8590*	-3,5640***	-2,1046**	-3,3603	-1,4418*
	(1,3484)	(1,4665)	(1,0689)	(1,0043)	(0,8825)	(2,1100)	(0,8319)
$\bar{R}^2$	0,3956	0,3939	0,3361	0,3800	0,3944	0,3236	0,3173
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 2 quarter horizon							
$\hat{\beta}$	-2,3865***	-2,2092***	-1,2001***	-0,5351	-1,1070***	-2,4385***	-0,9623
	(0,5960)	(0,7883)	(0,3884)	(0,7112)	(0,3739)	(0,6286)	(0,5857)
$\bar{R}^2$	0,6703	0,7426	0,6543	0,5895	0,6186	0,6415	0,6241
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 3 quarter horizon							
$\hat{\beta}$	-1,8846**	-2,4181**	-0,6840**	-0,3380	-0,4199	-2,3152**	-0,6916***
	(0,7642)	(0,8926)	(0,3005)	(0,5011)	(0,3266)	(0,8704)	(0,2252)
$\bar{R}^2$	0,7989	0,8056	0,7793	0,7352	0,7600	0,8061	0,7763
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 4 quarter horizon							
$\hat{\beta}$	0,3206	-0,0504	-0,0046	0,8706	-0,0029	-0,1739	-0,2952
	(0,5580)	(0,5089)	(0,2249)	(0,5875)	(0,3995)	(0,7123)	(0,1949)
$\bar{R}^2$	0,8255	0,8241	0,8697	0,7822	0,8240	0,8244	0,8744
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level. The values in parenthesis are the Newey and West (1986) corrected standard error of the estimates.

Table E.7: RMSE Out-of-Sample Forecasting Model 1 (including financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	4,8414**	6,0471**	(4,0049*)	4,3649***	4,1676**	4,1638	4,0909*
k=2	3,9408***	4,2825***	3,2196***	(2,8477)	3,1713***	3,5160***	3,0653
k=3	2,5491**	3,3392**	2,0248**	(1,7547)	1,8854	2,4988**	1,9742***
k=4	1,3790	(1,3163)	1,4522	2,1219	1,3247	1,3247	1,4856

Results are generated using equation $RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_{t,t+k} - y_{t,t+k})^2}$. Values in parenthesis indicate the lowest RMSE at each horizon.

Table E.8: In-Sample Regression Results Model 2 (including financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
GDP growth on a 1 quarter horizon							
$\hat{\beta}$	-4,4200***	-5,0646***	-1,8711	-2,9859**	-2,1352**	-3,8380	-1,5464*
	(1,4272)	(1,7263)	(1,2110)	(1,3783)	(1,0165)	(2,3978)	(0,8780)
$\bar{R}^2$	0,4238	0,3908	0,2775	0,4434	0,3821	0,2736	0,2619
F sig.	0,0001	0,0000	0,0004	0,0005	0,0004	0,0002	0,0001
GDP growth on a 2 quarter horizon							
$\hat{\beta}$	-2,0833**	-1,5180	-0,9746***	0,4735	-1,2213***	-2,6715**	-1,1111*
	(0,7816)	(0,9936)	(0,2687)	(0,3431)	(0,3872)	(0,9398)	(0,6230)
$\bar{R}^2$	0,6384	0,5878	0,5937	0,5373	0,5874	0,5876	0,5914
F sig.	0,0000	0,0000	0,000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 3 quarter horizon							
$\hat{\beta}$	-1,4720**	-2,1418**	-0,6075**	-0,0564	-0,3021	-1,8856***	-0,6917**
	(0,6318)	(0,8962)	(0,2765)	(0,5492)	(0,3562)	(0,6173)	(0,2969)
$\bar{R}^2$	0,7846	0,7887	0,7749	0,7432	0,7543	0,7962	0,7843
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
GDP growth on a 4 quarter horizon							
$\hat{\beta}$	0,2728	-0,0130	0,2148	0,6413	-0,0164	-0,3252	-0,2172
	(0,4655)	(0,3988)	(0,2879)	(0,6024)	(0,3450)	(0,4889)	(0,2659)
$\bar{R}^2$	0,8062	0,8050	0,8085	0,8322	0,8050	0,8064	0,8592
F sig.	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

The significance level of the spread coefficient is denoted with * when significant on a 10% level, ** on a 5% level and *** on a 1% level. The values in parenthesis are the Newey and West (1986) corrected standard error of the estimates.

Table E.9: RMSE Out-of-Sample Forecasting Model 2 (including financial crisis)

	Corporates all	Financials	Consumer G&S	Basic Materials	Industrials	Commodities	Technology
k=1	5,5395***	8,0972***	(4,0779)	4,5704**	4,3850**	4,3461	4,4675*
k=2	3,6950**	3,7196	2,9575***	(2,4377)	3,2877***	3,9010**	3,2350*
k=3	2,3355**	2,8500**	1,7726**	(1,5645)	1,6357	2,1120***	1,6815**
k=4	1,3790	1,3526	(1,3443)	1,6174	1,3546	1,3930	1,6178

Results are generated using equation $RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{y}_{t,t+k} - y_{t,t+k})^2}$. Values in parenthesis indicate the lowest RMSE at each horizon.