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Bond Spreads as Predictors of Economic Activity in Eight European Economies[1]

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Abstract

In this paper we examine the relationship between real activity and financial market tightness in Europe using data on 500 corporate bonds between July 1994 and May 2011 for Austria, Belgium, France, Germany, Italy, Netherlands, and Spain – and the United Kingdom. We evaluate the importance of bond spreads in predicting real activity at the individual country level, and find they are consistent predictors of real activity even when we include measures of monetary policy tightness, other leading indicator variables and factors extracted from a large macro dataset. Our results are consistent at different forecast horizons and are robust to different measures of the bond spreads. When we compare the predictive ability of the bond spread and the excess bond premium in individual countries within the euro area and outside the euroarea, we find that only the core European countries have similar predictive ability in the bond spreads. Other countries in the euro area, and the UK, do not have similar predictive ability in the bond spreads.

JEL: E32, E44, G12
Keywords: corporate bond spreads, external bond premium, economic activity

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Introduction

The global financial crisis that began in 2007 and the ensuing recession have spurred renewed interest in the relationship between tightness of financial markets and the business cycle. While the actions of central banks have reduced short-term interest rates and medium and long term bond yields, through quantitative easing (Gagnon *et al.* 2011 and Joyce *et al.* 2012), markets have revised risk premiums upwards since 2007 in response to the financial crisis, the deteriorating global economic outlook and uncertainty surrounding the European debt crisis. A number of studies have considered the effects of financial conditions on the real economy (c.f. Hatzius *et al*. 2010, Cardarelli *et al.* 2011, and others summarised in Kliesen *et al.* 2012). Philippon (2009) has argued the bond market may more accurately signal a future decline in real activity than other forward looking indicators because it anticipates rising defaults, but the net effect of changes in spreads on real activity is likely to depend on the quality of the borrower, and is likely to be more powerful in recessions, according to Faust *et al*. (2012).[3]

The most recent research on the relationship between bond yields and real activity has been has been conducted by Gilchrist, Yankov and Zakrajšek (2009), Gilchrist and Zakrajšek (2012) and Faust *et al*. (2012) on US bond market data. In contrast to previous papers, these contributions employ a bottom up approach that concentrates on careful selection of bonds to create a credit spread index that is not distorted by bonds with embedded options, or bonds that are illiquid. They ensure that the maturity structure corresponds to business cycle frequencies, rather than the very short term, offering an improvement on the approach taken by previous authors including Gertler and Lown (1999), Mody and Taylor (2004) and King *et al.* (2007) who used high yield spreads to predict real activity in the 1990s and 2000s. While these papers provide convincing evidence that bond spreads predict future changes to real activity in the United States, there is no corresponding information for Euroarea and the United Kingdom, the second and third largest bond markets respectively.[4] Our paper addresses this issue.

In this paper we generate a unique new database using data extracted from Bloomberg LP to construct a credit spread index using 500 corporate bonds issued in eight European countries from July 1994 to May 2011, following the Gilchrist and Zakrajšek (2012) approach. Our credit spread index is created from individual corporate bond data at the country level, and we refer to our index as the European Gilchrist and Zakrajšek spread (hereafter the EGZ spread). We evaluate the importance of our credit spread index versus measures of monetary policy tightness, leading indicators, and a large array of macroeconomic information using latent factors following the methods of Stock and Watson (2002a,b, 2006, 2010) and Marcellino, Stock and Watson (2003) to disentangle the contributions of tightness in bond markets to changes in real activity. We then purge bond spreads of the duration, coupon,

[3] For example, option adjusted spreads over equivalent maturity government bonds were 200 basis points higher in May 2012 than in July 2007 for investment grade borrowers in the United Kingdom, and spreads for sub-investment grade borrowers were approximately 500 basis points higher according to data on spreads for investment grade borrowers from Bank of America Merrill Lynch and Bank of England reported in the Bank of England Inflation Report, May 2012.

[4] European bond markets, which had $1263.4bn of outstanding corporate bonds in December 2011, of which $947.9bn were issued in euro and $315.5bn in sterling, are the second and third largest bond markets, respectively, after the United States, according to data from the Bank for International Settlements, Quarterly Review, March 2012.

amount outstanding, age and Moody's KMV distance to default measures to create excess bond premiums (hereafter the EBP).

This allows us to make several contributions to the literature on the relationship between real activity and financial market tightness. First, we can evaluate the importance of the EGZ spread and the EBP as predictors of real activity in Europe. This provides the first test of the Gilchrist *et al.* (2009a) and Gilchrist and Zakrajšek (2012) model using data from outside the United States. We find that EGZ and EBP measures are highly significant for predicting the growth in our four real activity measures at horizons ranging from one quarter to two years ahead. Concentrating on real GDP, these results are confirmed for individual countries in the euroarea and for the United Kingdom, and are robust to different measures of the bond spread. We find the spread is significant even after we include other indicators of economic confidence and sentiment in an attempt to control for anticipated changes in real activity. Moreover, we find that the EBP has greater influence on real GDP compared to the predictable part of the bond spread more closely related to default risk. EGZ and EBP measures are robust indicators of financial market tightness that predict changes in economic activity in Europe under a range of conditions, providing strong support for the Gilchrist *et al.* (2009a) and Gilchrist and Zakrajšek (2012) model.

Second, we exploit the cross sectional dimension of our data to disentangle the responses to the EGZ and EBP measures in different countries in Europe. There is a high degree of consistency in the forecasting power of EGZ and EBP measures at different horizons for each country, with a commonly signed negative coefficient when predicting real GDP growth. But the scale of the response is not equal. When we test for equality of coefficients on the bond spread across all European countries we reject the null, and for euroarea countries (excluding the UK) we also reject the null of equality. But for the euroarea core countries, Germany, France and Netherlands, we cannot reject the null that the coefficients on bond spreads are equal across these countries. This provides us with information about the differences in the sensitivity of different European economies to financial market tightness, and indicates that the euroarea core and the peripheral countries in our sample do not respond in an identical way to tightening credit spreads.

Finally, our results allow us to discuss the interpretation of the credit spread in the context of the literature on information asymmetry. Credit spreads have been interpreted by De Bondt (2004) as a response to the change in the firm's net worth following the financial accelerator model of Gertler and Gilchrist (1994) and Bernanke *et al.* (1999). The significance of the EGZ spread as a predictor of real GDP growth may demonstrate accelerator effects operating through variations in net worth of the borrower (c.f. Bernanke *et al.,* 1999; de Bondt, 2004; and Gilchrist *et al.*, 2009b), or available credit from financial intermediaries (c.f. Gertler and Karadi, 2009). Alternatively they may anticipate rising defaults as Philippon (2009) suggests, or 'risk shocks' emanating from the financial sector (Christiano *et al.*, 2010, and Alpanda, 2011). However, the significance of EBP which is purged of default risks using Moodys KMV measures of expected default frequency implies that there is more than risk of default at work here. Several authors have proposed that households may allocate assets by switching between riskier assets in a 'search-for-yield' and safer assets in a 'flight-to-quality' when they become more cautious due to 'portfolio shocks' (Heaton and Lucas, 1997; Bonaparte and Cooper, 2009), ‘volatility shocks’ (Fernandez-Villaverde *et al.* 2009) or ‘risk premium shocks’ (Kim, 2009. The EBP may therefore reveal when asset allocation decisions of investors, who are prepared to supply more credit through the corporate bond market at certain times and less so at others.

We conclude that bond spreads are useful predictors of changes in real activity even after we have controlled for measures of monetary policy tightness, leading indicators, economic sentiment, and a wide range of other macroeconomic variables summarized by latent factors. They reflect changes in net worth of the borrower and credit supply from the lender. Our evidence from European markets is robust to many different model specifications and supports previous findings from the United States.

The paper is organized as follows. Section 2 discusses the recent literature. We then explain our data in section 3 and the methodology we employ in Section 4. Section 5 provides forecasting results for real economic activity using bond spreads and the decomposition of bond spreads into the predictable component and the excess bond premium. We discuss the differences across European country blocks in this section. Section 6 then considers the forecasting results when we include credit spreads or their components, and the latent factors from a large macro database. Section 7 discusses the findings and concludes.

2. Literature

The recent financial crisis has injected new interest into the literature on bond spreads and economic activity because economic activity has declined during a Great Recession and because bond spreads have become more volatile after the collapse of Lehman Brothers in September 2008. The most recent research in US bond markets has been conducted by Gilchrist, Yankov and Zakrajšek (2009), Gilchrist and Zakrajšek (2012) and Faust *et al.* (2012) on US bond market data. In contrast to previous papers, these contributions employ a bottom up approach to the construction of spreads in order to remove the prepayment and liquidity risks, see Duca (1999).[5] Recognising that embedded options in callable bonds could substantially alter the information content of movements in corporate bond yields, these authors identify callable bonds and model the predictable part of the spreads separately for callable and non-callable bonds. They also remove the influence of small corporate issues or issues with a remaining term-to-maturity of less than one year or more than 30 years that are likely to influence the spread through the high liquidity premia. By using these selection criteria Gilchrist, Yankov and Zakrajšek (2009) and Gilchrist and Zakrajšek (2012) seek to improve on the measurement of bond spreads, which have previously taken a top down approach, and have been unable to select individual bonds.

[5] Prepayment risk, stems from the callability of bonds, and may result in higher yields to compensate the lender for the possibility that a firm will refinance existing debt with bonds offering lower coupon payments if conditions make a call option attractive. Liquidity risk is connected with the asset-liability matching of investors such as pension funds and insurance companies that buy and hold assets, seldom trading on the secondary market (see Alexander *et al.* 2000). The illiquidity of the market for corporate bonds as institutional investors acquire a larger proportion of the outstanding bonds can require additional yields to compensate other investors, as evidenced by Longstaff *et al.* (2005).

Gilchrist, Yankov and Zakrajsek (2009) construct a bond spread index from monthly data on prices of senior unsecured corporate debt traded in the secondary market over the 1990-2008 period, issued by about 900 U.S. nonfinancial corporations. They construct portfolio-based bond spreads (according to the issuer's expected probability of default, and use Moody's KMV EDF measure) which are shown to contain substantial predictive power for economic activity over a 12 month/4 quarter horizon. They also construct portfolios of stock returns, which serve as controls for news about firms' future earnings and examine the information content of bond spreads that is orthogonal to the information contained in stock prices of the same set of firms. They conclude that most of the predictive power of spreads comes from the middle of the bond-quality spectrum, a result also documented by Mueller (2009). They further assess the impact on the macroeconomy of movements in the bond spread in a structural VAR framework. They conclude that unexpected increases in the bond spreads cause large and persistent contractions in economic activity. Such bond market shocks explain 30% of the variance in economic activity at two- to four-year horizons.

Faust *et al.* (2012) adopt a similar method to Gilchrist, Yankov and Zakrajšek (2009) and Gilchrist and Zakrajšek (2012), but include bonds issued by financial firms as well as non-financial firms in their sample. After constructing the bond spread index, they regress the measure on a Moody KMV measure of distance to default and other variables to separate a predicted spread from the unexplained part, labelled the excess bond premium. Then, using a modelling approach similar to earlier dynamic factor models, they extract the first principal components from a database of 15 macroeconomic indicators and 110 financial indicators, which they use with bond spreads to predict real activity. The models are selected using a Bayesian Model Averaging method, and the preferred models assign the largest posterior weight to bond spreads for a range of different real activity measures such as real GDP growth, industrial production, personal consumer expenditure, business fixed investment, employment, unemployment, exports and imports. The use of option-adjusted bond spreads seems to improve forecast accuracy even in the 2007-2009 period.

These papers improve on an earlier literature that used information from corporate bond spreads over Treasuries, such as the Baa – Treasury spread, to predict real activity. While this spread contains information on the economic cycle from bond default risk they do not control for prepayment risks and liquidity risk which also varies over the business cycle. Gertler and Lown (1999) argued that high-yield bonds have a relatively large component that is due to bond risks, and a smaller component that reflects prepayment or liquidity risk, and are therefore better indicators than previous spreads. They show that the spread has explanatory power over the GDP growth gap one quarter and one year ahead between 1980Q1 and 1999Q1. Two further studies by Mody and Taylor (2004) using a quarterly index series of the yield on sub investment grade bonds between 1998Q1 and 2001Q4 and King *et al.* (2007) who use high yield bond spread at various maturities confirm this view. The poor performance of high yield spread more recently has called this into question.

Almost all of these studies were conducted on US data, where the bond market is large, and different ratings classes of bonds are well populated. There has been some work on predictions using bond spreads in Europe, by Davis and Fagan (1997) who tested for the predictive content of the bond quality spread (defined as the difference between private and government bonds) for three European countries individually (i.e. Denmark, Germany and the UK). They found a significant relationship for credit spreads only in Germany for inflation and output growth, however, the out-of-sample forecasting results were weak. De Bondt (2004) offered the first empirical examination of the balance sheet channel in the euro area since the introduction of the single currency. He approximated the external finance premium using the monthly average of daily observations of the spread between long-term BBB-rated euro area corporate bond yields and the 7 to 10 year- government bond yield over a short sample (January 1999 to June 2001). His results are indicative, that credit spreads are supportive of the balance sheet channel underpinning the financial accelerator model.

3. Data Sources and Characteristics

We employ the same bottom-up approach guided by Gilchrist *et al.* (2009a) and Gilchrist and Zakrajšek (2012) to construct a country level bond spread index from European bond level data. By using appropriate selection criteria suitably adjusted for European bonds, we construct the European Gilchrist and Zakrajšek (EGZ) measure of bond spreads, with the same advantages as the US studies.

There are three significant differences between US and European bond markets that distinguish our measures from Gilchrist and Zakrajšek (2012). The first and most obvious difference is that we consider eight different European bond markets for the eight countries in our sample (Austria, Belgium, France, Germany, Italy, Netherlands, Spain and the UK), in contrast to a single bond market in the United States. Seven of these countries have the same euro benchmark rate, but the UK market has the sterling benchmark. We create a unique country-specific bond spread index for non-financial outstanding senior unsecured bonds in these eight European economies and shed light on its predictive content for future real activity taking account of cross-country differences. This approach also differs from de Bondt (2004) in two respects. de Bondt aggregates the spreads of euro zone bonds into one euro-area index by averaging across countries, while we construct individual country bond spreads; and we include the United Kingdom as a non-euro area country with a sizable bond market in our study, where he excludes the UK because it does not have the same reference rate as his euro area countries.

The second difference with US studies is that very few European bonds are callable bonds, in contrast to the United States. In the Gilchrist and Zakrajšek (2012) sample, for example, two thirds of bonds are callable, while in our sample the proportion is just 9 percent of the total bonds issued are callable bonds. In our study, since the loss in the number of observations is manageable, we exclude callable bonds and also any putable bonds from the sample we use for each country to remove the problems associated with prepayment risk. Since we also remove the influence of small corporate issues or issues with a remaining term-to-maturity of less than one year or more than 30 years that are likely to influence the spread due to high liquidity premia, we are left with bond spreads that are more closely connected to default risk than top down measures.

The third difference relates to institutional characteristics in Europe compared to the United States. In Europe, the commercial paper market has only recently grown in size and only largest corporates and financial institutions access this market. Similarly, due to the smaller bond market in individual European countries, data availability for Baa or Aaa spreads are extremely limited over our sample. There is limited value from utilising the CP-Bill spread and the Baa-Aaa spreads in our studies, but their elimination is unlikely to have a substantial impact on our results, since Gilchrist and Zakrajšek (2012) concluded that these spreads provide little additional explanatory power in their results for US data when they include their bond spread. Instead we control for other spreads including the term spread and the real interest rate as defined in the next section.

3.1 Data

Our dataset for eight European countries consists of 500 straight corporate bonds during the period between July 1994 and May 2011. The countries - Austria, Belgium, France, Germany, Italy, Netherlands, and Spain - have been chosen to represent the largest economies in the euroarea, plus the United Kingdom, which has a large bond market outside the euroarea. The choice of the time span was imposed by data availability. We used Bloomberg L.P. to extract market data at bond and firm level and other macroeconomic data from various major international databases. Additionally, we used Moody's KMV database of Expected Default Frequencies (EDFs) at firm level to obtain a bond risk measure for the bond issuers in our sample.[6] The Moody's dataset consisted of the EDF data (which runs monthly from January 1992 until August 2010) and a mapping of Moody's unique PID (firms' personal identification code) with the company's name and ticker. We manually matched the bond issuers in our sample with the Moody's PID based on name and ticker (cross-checked between Moody's and Bloomberg) and assigned the respective EDF data. 81% (407 bonds) of our bonds had a PID code, but due to the different coverage of sampling periods between the two datasets, the final matched dataset consisted of 269 bonds (92 companies) across 176 time periods from January 1996 until August 2010.

Using the universe of domestic corporate bonds with Bloomberg coverage we select corporate bonds in Europe according to the same criteria as Gilchrist and Zakrajšek (2012), yielding a matched sample of 190 companies across 45 industry sectors. We refer to outstanding senior unsecured bonds issued by non-financial corporates in local currency with a fixed coupon schedule (no index-linked or step-ups). The bond data on yield to maturity, the fixed coupon rate, the full schedule of coupon payments at each pricing date are available for each bond issue and the zero-coupon continuously compounded euro and UK government benchmark rates are measured at monthly frequency. We exclude callable bonds, and, to mitigate the outliers' problem consistent with Gilchrist and Zakrajšek (2012), we ensure that all observations are in the range between 1.5 basis points and 2,800 basis points. This leaves us with 500 bonds, and we construct the EGZ spread as the difference between the actual yield to maturity of the bond and its corresponding theoretical risk-free yield.

We have other bond-specific data such as Macaulay duration, amount outstanding, amount issued, whether the bond has any embedded options, the issue and maturity dates,

[6] Moody's KMV provides the Expected Default Frequency measure—a forward-looking probability of default metric—which is available for quoted firms and sovereigns and is the market standard bond risk measure. The EDF measure is compiled using Moody's default database and leverages market data, industry, volatility, financial statement data, and historical default information in a proprietary financial model.

Standard & Poor's bond rating, market of issue, currency, issuer name, and the issuer's industry sector. This information is used to predict the EGZ spread, and to extract the excess bond premium.

The bond spread is defined as $S_{jit[k]} = y_{jit[k]} - y^{f}_{jit[k]}$ where $y_{jit[k]}$ is the yield of bond k issued by firm j of country i in month t, and $y^{f}_{jit[k]}$ is its corresponding theoretical risk-free yield calculated using the price as the sum of the present value of the bond's cash-flows discounted using the continuously-compounded zero-coupon Euro and GBP Benchmark curves. Also, the yields off the benchmark curves are linearly interpolated such that the maturity of a given cash-flow payment exactly matches the maturity of the spot rate that is used to discount that cash flow.

The bond spread index at the country-level in period t is then calculated as the arithmetic (or cross-sectional) average of all bond spreads in a given period for each country:

$$S_{it} = \frac{1}{N_t} \sum S_{jit[k]}$$

where i indexes the country, k indexes the bond, N is the number of bond observations in month or quarter t, and t is the time dimension.

We compare our constructed EGZ spread with the Z-Spread computed by Bloomberg, which is available from the second half of 2005. The Z-spread is defined as the spread that must be added to the respective zero-coupon swap rate curve so that a security's discounted cash flows equal its mid-price, with each dated cash flow discounted at its own rate. One of the major differences between the two ways of constructing the spread lies in that we use the euro benchmark and UK government zero-coupon curves continuously compounded while Bloomberg utilize the default Bloomberg swap curve at annual compounding frequency. After constructing a Z-spread index in a similar fashion to our EGZ spread, Figure 1 shows an extremely high correlation over the common sample period.

By contrast there is not a particularly close correlation between the EGZ spread and Bloom's uncertainty measure, Figure 2, which is constructed to measure European policy-related economic uncertainty from newspaper coverage of policy-related economic uncertainty, and disagreement among economic forecasters as a proxy for uncertainty (see Bloom, 2012). While both series pick up the spikes in 2001 and 2008, the uncertainty measure finds spike in 2003, which is missing in the EGZ measure and registers only a mild spike in uncertainty in 2010, when the EGZ spread hits its maximum value. This suggests that the EGZ measure is not a primarily a measure of economic uncertainty.

Explanatory variables used with our constructed EGZ spreads to explain real activity include the term spread, the real interest rate, consumer confidence, economic sentiment, and a composite leading indicator variable. The term spread is defined as the difference between the 10-year generic government bond yield and the 3-month generic government bond and the real interest rates is defined as the difference between the official nominal interest rate (published by the ECB and Bank of England respectively) and the inflation rate obtained from IMF's IFS database. The generic government bond yields are the country-specific benchmark bond yields of constant maturity available from Bloomberg. Consumer confidence represents the arithmetic average of the answers (balances) to four questions on the financial situation of households and the general economic situation (past and future) together with that on the advisability of making major purchases. Economic sentiment reflects general economic activity of the EU. This indicator combines assessments and expectations stemming from industry, consumers, construction and retail trade. The two sentiment indicators are published by the European Commission and available via Bloomberg. The OECD Composite Leading Indicator (CLI) series are available for each country at monthly frequency on the OECD website. The series used in our analysis is the amplitude adjusted series. The OECD CLI is designed to provide early signals of turning points (peaks and troughs) between expansions and slowdowns of economic activity. The component series for each country are selected based on various criteria such as economic significance, cyclical behavior, data quality, timeliness and availability.

3.2 Descriptive Statistics

Table 1 reports there are 19,574 bond-firm observations in our sample. The mean firm in our sample has between 4 and 5 senior unsecured issues outstanding in any given month, with the majority of the firms having less than 10 issues trading in the secondary market at a point in time. Compared to the US sample of bonds of Gilchrist and Zakrajšek (2012), the average firm in Europe has twice as many bonds outstanding compared to the average US firm, but the US distribution has a higher maximum of 74 bonds per firm, compared to a maximum of 13 bonds per firm in Europe, which suggests intensive users of the bond market in the US issue many more bonds than their counterparts in Europe.

The bonds have an average actual nominal yield of 4.87% and an average artificial yield of 3.16%. The average coupon rate in the sample is 5.36% with a maximum of 8.88%. The corporate bond spread has a minimum of 1.5 basis points and a maximum of approximately 2,800 basis points. An average bond has an expected return of 170.72 basis points above the comparable risk-free artificial bond and a standard deviation of 152.5 basis points, which reflects the wide range of the bond quality in our sample[7]. Compared to the US sample of bonds of Gilchrist and Zakrajšek (2012), the average market yield in the US is almost 3 percentage points higher than for the average firm in Europe, which probably reflects the longer sample period, embracing the Great Inflation period, when yields were higher. We are not interested in the yield *per se*, but in the bond spread, and once averaged the bond spread index in Europe has a mean of 140.3 basis points above the risk-free rate.

In terms of default risk as measured by the S&P bond ratings our sample spans almost the entire spectrum of bond quality from financially vulnerable firms rated B- to secure firms rated AA, compared to a broader distribution of ratings in from D to AAA in the US. The bond spread is higher by around 30 bps in the US, which probably reflects the greater number of sub investment grade (junk) bonds in the US sample.

The distribution of the amount of debt outstanding of these issues is positively skewed, with the range running from €7.7 million to €3.2 billion. The average duration is shorter and equal to approximately 7 years, as all bonds in our sample pay regular non-zero coupon

[7] The equivalent Bloomberg Z-Spread index has a mean and standard deviation of approximately 143.7 bps.

payments over their life. The maturity of the issues in our sample is long, with an average maturity at issue of 12.6 years and an average remaining term-to-maturity of 9.7 years. The

Table 1.

Variable	Obs.	Mean	Std. Dev.	Min	Max
No. of bonds/firm	19574	4.91	3.26	1	13
Actual market yield	19574	4.87	1.73	0.30	29.85
Theoretical yield	19574	3.16	1.17	0.41	8.44
Bond Spread (bps.)	19554	170.72	152.5	1.50	2794.74
Bloomberg Z-spread (bps.)	13958	142.27	143.6	0.01	2338.01
Coupon (%)	19574	5.36	1.19	0.5	8.875
Amount outstanding (€mil.)	19574	614	405	7.73	3,270
Amount issued (€mil.)	19574	643	425	10	3,500
Duration (yrs.)	18988	7.06	3.39	0.79	16.79
Term to maturity (yrs.)	19574	9.66	6.68	1.04	31.98
Age (yrs.)	19439	2.94	2.61	0	16.78
Maturity at issue (yrs.)	19574	12.58	7.35	3	40.03
S&P rating	17311	-	-	B-	AA

Notes: Sample period July 1994 – May 2011; No. of bonds = 500; No. of firms = 190; No. of months = 203; No. of industry sectors = 45; No. of bonds/months for Austria (33/69), Belgium (24/96), France (207/116), Germany (61/101), Italy (46/107), Netherlands (45/92), Spain (10/88) and UK (74/203). There are 2 observations with a bond spread of less than 5 bps and 67 observations (12 bonds) that have a term to maturity higher than 30 years. The bond spreads for these observations is however within the range of the full bonds sample and have therefore been included.

average duration, term to maturity and maturity at issue are relatively similar across the US and Europe samples.

Table 1 also presents the additional country level variables used to explain real activity. These variables are used to establish that the predictive power of bond spreads is not driven by the same information contained in other measures such as government yields or short term interest rates. Therefore we include the term spread and the short-term real interest rate in our model. In order to control for common factor trends across the sample countries, we take the mean values for the term spread and the real interest rate at every time period across the 8 countries. The term spread has a mean of 1.5% and a maximum of 3.37% with a standard deviation of 1.18%. The real interest rate has a mean of 1.26% and a maximum of 6.3%.

We also add information from consumer confidence and economic sentiment. The consumer confidence indicator has a mean of -9.8 with a minimum of -47.6 and maximum of 20.3. The economic sentiment indicator has a mean of 100.1, a minimum of 65.4 and a maximum of 117.3. The pair-wise correlation between the bond spread index and the consumer confidence and economic sentiment indicators are -0.3 and -0.6 respectively, while the correlation between the consumer confidence and economic sentiment indicators is 0.7. The OECD CLI has a mean of 100.4, a minimum of 85.6 and a maximum of 105.8. The correlation between the bond spread index and the CLI index is -0.49, while the correlations between the CLI and the consumer confidence and economic sentiment indicators are approximately 0.55 and 0.79, respectively.

The highest correlation in absolute terms is between the real short-term interest rate and the term spread at approximately 0.8. As expected, the bond spread exhibits negative correlations with industrial production, employment stock and real GDP growth and positive correlation with unemployment rate. The correlation between the bond spread index and the real interest rate is -0.2 at the 3- and 12-months horizons and approximately -0.03 at the 24-months horizon. The correlation between the bond spread index and the term spread is 0.3.

4. Methodological Issues

To assess the predictive ability of bond spreads we use the forecasting specification in which the contemporaneous value of the bond spread is used to forecast the change in real economic activity over the following *h* periods. The forecasting specification is:

$$\Delta^h Y_{it+h} = \alpha + \beta * S_{it} + \sum_{k=1}^{5} \gamma_k * X_{itk} + u_i + e_{it+h}$$

where $\Delta^h Y_{it+h}$ is the growth rate of the economic activity indicator, namely manufacturing industrial production index, unemployment level, employment stock, and real GDP.[8] Subscript *h* denotes the forecast horizon (i.e., *h* = 3, 12, and 24 months for monthly data; and *h* = 1, 4, and 8 quarters for quarterly data).

S_{it} denotes the bond spread index constructed as the difference between the actual yield to maturity of the bond issue and its corresponding risk-free rate, $S_{jit[k]} = y_{jit[k]} - y^f_{jit[k]}$, where *i* =(1,..., 8) indexes the country, and *t* captures the time dimension. X_{itk} is a set of *k* = 5 control variables (e.g. the term spread, the real short-term interest rate, the consumer confidence, economic sentiment and composite leading indicators for each country) that provide predictive ability of future real activity. u_i represents the country-specific intercept (fixed effect) allowing for unobserved heterogeneity. e_{it+h} is the idiosyncratic forecasting error, where $u_i + e_{it+h}$ is also known as the composite error. α, β and γ_k are coefficients..

We have already noted that the CP-Bill spread and the Baa-Aaa spread have diminished predictive power over real activity in the most recent studies, despite their strong performance in earlier decades. Therefore, we follow Gilchrist and Zakrajšek (2012) by including the term spread and the real interest rate to predict real activity. The choice of these variables refers to an earlier literature by Harvey (1988), Estrella and Hardouvelis (1991), Estrella and Mishkin (1998) and Hamilton and Kim (2002), where these spreads were used.

We include measures of consumer confidence, economic sentiment and a composite leading indicator variable to measure forward looking indicators of real activity.

4.1 The EBP and the decomposition

[8] The log growth rate of *Y* in country *i* between period *t* and *t+h* is defined as: $\Delta^h Y_{it+h} = \frac{c}{h+1} ln\left(\frac{Y_{it+h}}{Y_{it-1}}\right)$. *c* is a scaling constant that depends on the frequency of the data (e.g., c = 1200 for monthly data, and c = 400 for quarterly data).

Since we have eliminated the callable bonds in our sample to avoid using mispriced bonds with embedded options, this greatly simplifies our decomposition of the spread into the predicted spread and the excess bond premium.

We make the assumption that the log of the bond spread on bond *k* issued by firm *j* in country *i* at time *t*, $\ln S_{jit}[k]$, is related linearly to a firm-specific measure of expected default, EDF_{jit}, and a vector of bond-specific characteristics, $Z_{jit}[k]$, according to the specification below:

$$\ln(1+ S_{jit}[k]) = \alpha + \beta * \ln(1 + EDF_{jit}) + \gamma * \ln(Z_{jit}[k]) + \varepsilon_{jit}[k]$$

The vector of bond-specific characteristics captures liquidity and tax premiums and it includes mid-Macaulay duration, $DUR_{jit}[k]$, the amount outstanding, $AOS_{ji}[k]$, the fixed coupon rate, $CPN_{ji}[k]$, and the age of the bond issue, $AGE_{jit}[k]$ following Gilchrist and Zakrajšek (2012) and King and Khang (2005).

Taking logs of the bond spread and the EDF provides a useful transformation to control for heteroskedasticity, given that the distribution of the two variables is highly skewed. As the bond spread, the EDF and the coupon rate represent very small values in percentages, taking the direct log transformation of these variables would result in negative values, therefore, we add unity before taking logarithms. In this case, the percentage change interpretations are closely preserved and it is acceptable to interpret the estimates as if we used the logarithm of the variable (Wooldridge, 2006).

The specification is estimated using OLS at bond level at monthly frequency, with multi-way clustering of standard errors at both country (i) and time (t) dimensions (Cameron et al., 2011). The resulting standard errors are thus robust to arbitrary within-panel autocorrelation (clustering on country) and to arbitrary contemporaneous cross-panel correlation (clustering on time). There is no point in using 2-way cluster-robust standard errors if the categories are nested, because the resulting standard errors are equivalent to clustering on the larger category. The regression also includes industry and bond rating fixed effects. Industry fixed effects control for all variables that are constant over time but specific to each industry such as expected recovery rates across industries. Bond rating effects capture soft information that is complementary to the market-based measure of default risk (Löffler, 2007).

Therefore, in our case, assuming normally distributed disturbances, we obtain the (antilog) point prediction for the bond spread for bond *k* of firm *j* in country *i* at time *t* as follows:

$$\hat{S}_{jit}[k] = \exp\left(\hat{\beta}\ln(1 + EDF_{jit}) + \hat{\gamma}\ln Z_{jit} + \frac{\hat{\sigma}^2}{2}\right) - 1$$

where $\hat{\beta}$ and $\hat{\gamma}$ are the OLS estimates of the corresponding parameters and $\hat{\sigma}^2$ is the estimated variance of the disturbance term, $\varepsilon_{jit}[k]$.

Having obtained our measure of the predicted spread as the fitted values from the specification above, we can now define the excess bond premium as the difference between the actual bond spread of bond *k* issued by firm *j* in country *i* at time *t*, and the predicted spread of the same bond at time *t* as follows:

$$EBP_{jit}[k] = S_{jit}[k] - \hat{\hat{S}}_{jit}[k]$$

This linear decomposition takes place at bond level such that both the predicted spread and the EBP are bond-specific. We then take the cross-sectional average across bonds in country *i* at time *t*, and construct a country-level index for the EBP and the predicted spread as follows[9]:

$$\hat{S}_{it} = \frac{1}{N_t} \sum_j \sum_k \hat{S}_{jit}\,[k]$$

and

$$EBP_{it} = \frac{1}{N_t} \sum_j \sum_k EBP_{jit}\,[k].$$

5. Results

For robustness, we estimate the equations using pooled OLS, fixed effects and random effects. The pooling assumption treats the spreads in these European countries as identical, while the fixed effects recognises unobserved heterogeneity in the spreads that is related to the country group, and random effects recognises unobserved heterogeneity that is unrelated to the country group i.e. randomly assigned. We have no priors on which assumption is likely to be correct, since although there are systematic differences between European countries in the yields of corporate and sovereign bonds, we cannot be certain that there are differences in the spreads between them. The Breusch and Pagan Lagrangian multiplier test determines whether a fixed and random effects model is preferred to the pooled OLS model, while a robust version of the Hausman test is used to distinguish between fixed and random effects.

By constructing the dependent variable as the growth rate over the next *h* periods of an economic activity indicator we introduce serial correlation in the error terms within a country, which will cause least squares to yield inconsistent estimates of the standard errors and thus lead to invalid inference. To take into account this overlapping structure we use Newey West (1987) standard errors. We also use Driscoll-Kraay (1998) standard errors that are Newey-West-type standard errors to allow for autocorrelated errors across countries.

5.1 Prediction with the European (EGZ) Bond Spread

Table 2 determines the predictive ability of bond spreads for four different real activity measures – industrial production, the unemployment rate, the growth in employment, and real GDP – at the 12 month or 4 quarter horizon. We use the term spread to measure the slope of the yield curve, which we expect to have an expansionary effect on real activity, since a higher value (upward sloping yield curve) implies current short rates are below the future expected short rates consistent with a higher long rate. The real interest rate represents the real cost of capital, and a higher rate is expected to be contractionary. The EGZ bond spread is a measure of the cost of bond finance over and above the risk free rate, and again a higher rate is expected to be contractionary. These expectations are confirmed in Table 2 since the industrial production index, employment growth and real GDP fall as the EGZ bond spread rises, and unemployment

[9] Our approach in constructing the EBP and the predicted spread differs slightly from Gilchrist and Zakrajšek (2012). While they define the EBP as the difference between the averaged bond spread and the averaged predicted spread, we perform the decomposition at bond level since we do not have complete data for every bond characteristic at every point in time, which would have resulted in averaging out different samples of bonds.

rate rises. The impact of the bond spread is significant in all but one case, and the magnitude of the estimated parameters is similar across the three different estimation methods. The term spread and the real interest rate have the expected signs in most cases, but their coefficients are insignificantly different from zero in all but a few places.

Comparing our results with Gilchrist and Zakrajšek (2012) we find that all four real activity measures in European economies show similar directional changes in the bond spread when compared to the US, but the magnitudes are somewhat different. For example, a 100 basis point increase in the spread results in a 2.8 percentage point decrease in industrial production in our eight European countries, while in the US a 100 basis point increase in the bond spread results in a 3.8 percentage point drop in industrial production. Differences in magnitudes could be due to the sample periods used for the US studies (1973M1 – 2010M9) versus our European study (1996M1 – 2010M8). While both samples include the Great Moderation and the volatility of the global financial crisis, the European sample does not include the Great Inflation of the 1970s. However, when we compare magnitudes for real GDP, we find greater similarity. A 100 basis point increase in the spread results in a 1.25 percentage point fall in real GDP in the US, and a 1.36 percentage point drop in real GDP in the European economies. For the remainder of this section we discuss our real GDP results.

Table 3 considers the choice of the forecast horizon, focusing on real GDP growth. The three panels of the table consider the predictive ability at a shorter horizon (1 quarter), a medium horizon (4 quarters) and a longer horizon (8 quarters). We report results for the fixed effects model, which is selected by the diagnostic tests over random effects and pooled OLS alternatives. The results are consistent with our findings in table 2 at the 4 quarter horizon: the bond spread is significant at all three horizons with the expected negative sign, the term spread and the real interest rate are insignificant and with the expected signs with one exception.

In this model we add three further forward-looking measures, consumer confidence, economic sentiment and the OECD composite leading indicator measures recorded within each country in our sample. The financial accelerator model predicts that bond spreads should still have a significant predictive ability of future real activity even when other predictors of future activity, such as business and consumer sentiment or composite leading indicators, are included in the model. While all these variables should anticipate to some degree the onset of a recession and the deterioration in real economic conditions, the financial accelerator model also suggests bond spreads have an independent effect on future output because of their impact on investment. Therefore, if our bond spread variable remains significant when we add the other leading indicator variables, we have confirmation that the bond spread influences real activity through the balance sheet channel. This is indeed the case, since in every column in Table 3 the coefficient on the EGZ bond spread is significant.

In the second column for results at each horizon, we test whether the other indicators of expansion or contraction add explanatory power to our regressions when the bond spread is included. The results indicate that consumer confidence has the expected positive coefficients and it is strongly significant at all horizons, while economic sentiment has the expected sign at short horizons, but is insignificant and changes sign at longer horizons. The coefficient on the OECD composite leading indicator is significant with a positive sign, as expected, for all three forecast horizons. When we include these additional measures we find that the bond spread does not lose any of its significance, although its magnitude of its coefficient becomes smaller as the additional regressors are included in the model. This provides evidence supporting the influence of the bond spread through the balance sheet channel.

5.2 Prediction with the Excess Bond Premium

We now decompose the bond spread of bond k issued by firm i in month t, into the predicted spread and the excess bond premium. Table 4 reports the results of the regression of the bond spread on the expected default measure and other bond characteristics such as the coupon, the duration of the bond, the amount outstanding, and the age of the bond in order to estimate the predicted spread. We also include industry fixed effects and bond ratings to measure the issuing firm's financial health. The excess bond premium is constructed as the difference between the actual and the predicted spread from this regression model. Due to the fact that we have excluded the callable bonds from our sample, we do not need to evaluate the impact of the level, slope and curvature of the term structure on the bond spreads making our models simpler to estimate. We evaluate two specifications, the first includes the variables mentioned above as regressors, and the second adds the square of the expected default measure to allow for a quadratic relationship between the spread and the expected default measure.

When we examine the results in Table 4, we find that the default measure has a significant positive influence on the spread (column 1) indicating that investors require to be compensated for the probability of default, but the square of this term is also significant (column 2), and this has a negative sign, suggesting a convex relationship between the spread and the default probability. Since the Moodys KMV EDF is shown by Christiano *et al*. (2010) to be highly correlated with their risk shock, and the EDF has the dominant role in our regression predicting the EGZ spread, we can take the predicted part of the spread as a measure of risk shocks. Other variables are significant but less important in both specifications: the coupon has a positive and significant coefficient, while the age of the bond has a small positive effect, although duration and amount outstanding do not appear to be significant determinants of the spread. The fixed effects for industry and ratings are significant, and we can reject the hypothesis that the coefficients on these variables are jointly equal to zero.

The fitted equation in Table 4 (column 2) has a goodness of fit statistic of 0.47, and we use this to predict the spread, leaving the excess bond premium as the residual from this regression. Figure 3 shows the predicted and actual spread and Figure 4 shows the excess bond premium over our sample. Probably the most striking feature in these figures is the close resemblance between the actual bond spread and the EBP series which constitutes evidence that the EBP is actually the source for most of the bond spread's predictive content. This will also be indicated more formally by the regression results presented in the next section. We can note sharp increases in the EBP prior to and during the economic downturns captured by our sample period (namely, the early 2000s and the 2007-2009 recessions). The EBP falls to a historically low level in early 2003 and remains comparatively low for the following years as well. In July 2007, corresponding with the start of the financial crisis, the EBP starts increasing rapidly up to just above 2 percentage points at the end of 2008-early 2009. We note a second surge shortly after in the context of market-wide concerns of the viability of major financial institutions and an emerging European sovereign debt crisis.

Table 5 evaluates the prediction of the real GDP growth rate using the decomposed bond spread in a fixed effects regression at 1, 4 or 8 quarter horizons. We include the term spread, the real interest rate and report results with and without the other measures of economic conditions, consumer confidence, economic sentiment and the OECD composite leading indicator for each country. Our findings show that the term spread and the real interest rate variables are not significant in our regressions at horizons of 1, 4 or 8 quarters. The predicted part of the bond spread also is insignificant at all horizons, but the EBP has a negative and significant sign that shows consistent predictive performance of real GDP growth. The magnitude of the effect is comparable to the coefficient reported in the US study by Gilchrist and Zakrajšek (2012), since they found a 100 basis point increase in the EBP would result in a 2 percentage point decrease in real GDP growth in the US, and here we find a 100 basis point increase in the EBP would result in a 1.6 percentage point decrease in real GDP growth in our eight European countries at the four quarter horizon.

Part of the reason that the predicted spread ceases to be important for prediction of real GDP growth at all three horizons in our results is that it does not show much variation except for the period 2002-03. It is not altogether surprising to find that the fitted element of the spread was not significant in explaining the spread, but the unexplained part retained significance.[10] The result is entirely consistent with the findings for US data, where the predicted spread had no forecasting power from the mid-1980s onwards, but the EBP was a robust predictor of real GDP growth.

Other measures of economic sentiment, consumer confidence and the OECD composite leading indicator continue to predict real GDP growth at the 1, 4 and 8 quarter horizons. The OECD measure has greatest marginal impact, as measured by the coefficients and is consistently significant at all horizons. The consumer confidence index and the economic sentiment indicator have varying degrees of significance at each horizon. Economic sentiment has a negative sign, contrary to expectations.

5.3 Interpreting the EBP

The EBP series is very similar to the US excess bond premium calculated by Gilchrist and Zakrajšek (2012). The US EBP reached a record high of 2.75 percentage points in October 2008, therefore the magnitude of the EBP spike during the crisis was higher in the US than in Europe, and the European spike occurred after the spike in the US, suggestive of a "ripple" effect. The interpretation of the credit spread in the context of the literature on information asymmetry can be taken as response to the change in the firm's net worth following the financial accelerator model of Gertler and Gilchrist (1994) and Bernanke *et al.* (1999). The widening of bond spreads may reflect idiosyncratic shocks to net worth, which de Bondt calls 'balance sheet' effects, discussed in a structural DSGE context by Gilchrist *et al.* (2009b) and Christiano *et al.* (2010). The significance of the EGZ spread as a predictor of real GDP growth under this interpretation would demonstrate accelerator effects operating through variations in net worth of the borrower (c.f. Bernanke *et al.,* 1999; de Bondt, 2004; and Gilchrist *et al.*, 2009b). It

[10] In results that are not reported here, we find that if the composite leading indicator is dropped from our regressions explaining real GDP growth at different horizons, the predicted spread regains its significance. The correlation between the predicted spread and D4.CLI is approximately -0.09.

could also, arise due to variations in the availability of credit from financial intermediaries (c.f. Gertler and Karadi, 2009).

Alternatively, credit spreads may be important because bond markets are attuned to likely changes in default probabilities with deteriorating economic conditions as Philippon (2009) suggests, or because they reflect risk factors other than shocks to net worth, as reflected in Christiano *et al.* (2010) and Alpanda (2011). These risk shocks, derived in their case from variations in the stock price, are strongly correlated with the Moodys KMV measure of default. In our paper we decompose our EGZ spread into the predictable part that is mostly determined by the EDF from Moodys KMV, and the unpredictable part, which is the residual. It is the latter part not the former part that explains most of the future change in real GDP growth in our results, which suggests it is the part of the spread attributed to the deviations in the pricing of corporate bonds relative to the expected default risk of the issuer that matters. Since their risk shocks map closely to expected default risk, in Europe these shocks have a relatively benign influence on real activity – expected default risk is not the main cause of widening spreads and subsequent changes to real activity. The greater influence comes from the unpredicted part.

The unpredictable part labelled EBP may be due to a switch between 'search-for-yield' on riskier assets and 'flight-to-quality' when investors become more cautious due to 'portfolio shocks' (Heaton and Lucas, 1997; Bonaparte and Cooper, 2009), dislike among investors of 'volatility shocks' (Fernandez-Villaverde *et al.* 2009) or 'risk premium shocks' (Kim, 2009), showing us when investors decide they are willing (unwilling) to hold risk assets, including corporate bonds. Changes in attitudes can adjust the available supply of credit directly provided by the bond market (c.f. Adrian *et al*. 2010; Gertler and Kiyotaki 2010; He and Krishnamurthy, 2010; Gertler and Karadi 2011; and Brunnermeier and Sanikov, 2011). Under this interpretation they provide indications of tightening credit as the price of credit reflects the behavior of investors to asset allocation.

We find the extracted credit spreads EGZ and EBP have a correlation coefficient of just 0.47 with the uncertainty measures constructed by Bloom (2009, 2012), suggesting that they are not proxies for uncertainty over the future direction of policy.

5.4 Differences in the response to the EGZ spread and EBP across Europe

The purpose of Tables 6 and 7 is to compare the differences in the predictive ability of the EGZ bond spread and the decomposition into predicted bond spread and excess bond premium on the real GDP growth across different countries, exploiting the cross sectional dimension of our panel. In Table 6 there is a high degree of consistency in the predictive ability at different horizons for each country, but the magnitudes are clearly different. When we test for equality of coefficients on the bond spread across all countries we reject the null and when we consider only euroarea countries (excluding the UK) we also reject the null of equality. But for the euroarea core countries, Germany, France and Netherlands, we cannot reject the null that the coefficients on bond spreads are equal across these countries. Very similar results are obtained in Table 7, but here there is significance of the excess bond premium for all countries at 1 and 4 quarter horizons, and similar findings regarding the equality of EBP coefficients across countries. Not only might we anticipate different magnitudes of the spreads across Europe, but for much of the non-core we find the output growth response to these spreads is greater than in the core, magnifying the effect. This points to significant differences in the response to credit risk between the euroarea core and the periphery countries as well as between the euroarea and the UK.

6. Further Results with a Large Data Set

In this section we aim to evaluate whether the credit spread index and its components retain their predictive ability documented in the previous sections after we control for a wide series of macroeconomic and financial variables. This acknowledges that using a small number of leading indicators may reflect only specific shocks over certain periods of time, and at the same time underlines the usefulness of a large dataset. Factor models can usefully reduce the high-dimensionality problem by modelling the co-variability of the series with a small number of unobserved latent factors.

The selection of our dataset is guided by Marcellino, Stock and Watson (2003), who construct and compare both country-specific and EMU-wide dynamic factor models from OECD data to evaluate the homogeneity of the EMU countries. Unfortunately, the vast majority of the series used in their exercise have been discontinued or redefined, therefore the current data set reflects the availability for the countries concerned supplemented by other variables used in Faust *et al.* (2012), Hatzius *et al.* (2010), and De Bondt and Hahn (2010). We have extract between 58 and 69 variables at monthly frequency from 2001-2010 for each of the eight European countries in our sample from Bloomberg. [11] Data include disaggregated production, sales, new orders, consumer and producer prices, monetary aggregates, savings and credit, short and long-term interest rates, effective exchange rates, the exchange rate with the US dollar, international trade, components of the balance of payments surveys of private sector expectations, stock and commodity price indices and spreads. Details of the data series and the factor loadings can be found in Bleaney *et al.* (2012).

Following Marcellino, Stock and Watson (2003), the data are first transformed to achieve stationarity by taking logs and differencing. We apply the same transformations to all variables of the same type. We then test for seasonality using the robust F-test for the significance of regressors in a regression of the variables on seasonal dummies. If seasonality was detected, we further tested using the X-12 ARIMA F-tests for seasonality. The final decision was based on the combined test for the presence of identifiable seasonality as part of the X-12 ARIMA output.

We then seek to determine the correct number of static factors, r, using several commonly used methods. First we observe the screeplot of eigenvalues in descending order of their magnitude against their factor numbers and determining where they level off, introduced by Cattell (1966). The break between the steep slope and the levelling off portion indicates the number of meaningful factors, different from random error. Second, Stock and Watson (2002a,b) suggest to determine the number of factors by minimizing a particular information criterion and Bai and Ng (2002) further extend the study of information criteria to determine

[11] The number of variables across countries varies due to some being available at quarterly frequency, some being excluded due to a short time span, and some not being available at all.

the optimal number of factors as a trade-off between the goodness-of-fit and overfitting. Ahn and Horenstein (2009) build on the theoretical results of Bai and Ng (2002) and propose estimating *r* as the maximum of the ratio of two adjoining eigenvalues. Their Monte Carlo simulation results suggest this may be a promising new approach that sidesteps the arbitrary choice of the penalty factor in the Bai and Ng (2002) information criterion approach (as explained by Stock and Watson, 2010). These two criteria suggest using 3 factors for all countries, with the exception of Belgium and the UK for which only 1 factor is selected, and Spain for which 4 factors are selected. Third, as per the Forni *et al.* (2000) criterion, if the marginal explained variance is set at 10%, then only three factors are chosen consistently for all eight countries. Lastly, when deciding on the number of factors we also consider the meaning of the factors by looking at the squared rotated factor loadings. We find higher-order factors (i.e. from factor 9 onwards) either have very small loadings or they load on a variety of single variables. Therefore, for the purpose of our estimation we choose a maximum of 9 factors. The earlier empirical literature for European countries and the US generally seems to agree on six static factors (Artis *et al.,* 2005 and Marcellino, Stock and Watson, 2003 for UK and Euro-area; Stock and Watson 1999 and 2002a,b for the US). For homogeneity we proceed with 4 factors in all country models and we also consider models with 7 and 9 factors for robustness. The squared rotated factor loadings (see Bleaney *et al.* (2012) for details) show the estimated factors appear to be related to relevant subsets of the variables and we therefore interpret the factors according to the clusters of variables with the highest loadings. We suggest 1. An interest rate (IR) factor loading mostly on: the nominal interest rate, LIBOR 3-months rate, and the immediate call money total bank rate. 2. An exchange rate (ER) factor loading mostly on: CPI-based real effective exchange rate, the nominal and real effective exchange rate (narrow and broad). 3. A real prices (P) factor loading mostly on: PPI (energy, manufacturing and industrial), HICP and Brent crude oil price. 4. A market risk (MR) factor loading mostly on: the S&P dividend yield, the VIX, the LIBOR-OIS spread, and the 5-year CDS rate of major European banks. 5. A stock price index (SPI) factor loading on: Wilshire, Eurostoxx, S&P500. 6. A net trade (NT) factor loading on: intl. trade net trade value total. 7. A retail trade (RT) factor loading on: retail trade value and volume. 8. A CPI factor loading on: CPI excluding food and energy. 9. An M1 factor loading on M1.

We now evaluate the predictive content of the credit spread index for future real activity against the extracted factors from the previous section. Using the same forecasting specification as before with our main variable of interest (the credit spread or its components) and up to nine principal factors:

$$\Delta^h Y_{it+h} = \alpha + \beta * S_{it} + \sum_{k=1}^{9} \gamma_k * F_{itk} + u_i + e_{it+h}$$

where $\Delta^h Y_{it+h}$ is the real GDP growth with h denoting the forecast horizon, $i = \{1, \dots, 8\}$ indexes the country, and t captures the time dimension. S_{it} denotes the credit spread index (which will be replaced by its two components, the predicted spread and the EBP, in the following section). F_{itk} is a set of k = 9 estimated principal factors. All other variables are identical to our earlier model.

All regressions are based on panel data between September 2001 and May 2011 and are estimated by fixed effects. The results are presented in Tables 8 and 9 reporting performance over the same forecasting horizons as before for the models with 4, 7 and 9 factors.

Table 8 investigate the predictive content of the EGZ spread when we include the principal factors from our large macroeconomic dataset for real GDP growth at the 1-, 4- and 8-quarter horizons. The coefficients on the EGZ spread are highly statistically significant and with the expected negative sign in all specifications. There is a general improvement in the goodness of fit with an increasing forecasting horizon and also with increasing the number of factors. We can identify certain factors that show strong statistical significance, such as the IR and ER factors but our main concern is to determine whether the EGZ spread retains its predictive ability when we include principal components of a large macro data set. We find that the credit spread index remains a significant and robust predictor of future economic activity and has additional explanatory power at all forecast horizons.

Table 9 reports the significance of the credit spread's components against the principal factors for real GDP growth at the 1-, 4- and 8-quarter horizons. The coefficients on the EBP are highly statistically significant and with the expected negative sign in all specifications. The predicted spread component has limited independent explanatory power especially at the 8-quarter horizon where the EBP accounts for most of the predictive content of the credit spread. There is a general improvement in the goodness of fit with an increasing number of factors especially at the 4- and 8- quarter horizons. The IR, ER and M1 factors are significant with the correct signs mostly at the 4- and 8-quarter horizons.

We conclude that our results are robust to the inclusion of a wide array of additional variables summarized by factors.

7. Conclusions

In this paper we examine the relationship between real activity and financial market tightness in Europe. We evaluate the importance of bond spreads, and excess bond premiums extracted by removing the predictable part of the spread, in predicting real activity at the individual country level. By comparison with other measures of monetary policy tightness and signals from leading indicators of economic performance, we find that the bond spreads and excess bond premiums consistently predict changes in real activity. These findings are consistent at different forecast horizons and are robust to different measures of the bond spreads. When we compare the predictive ability of the bond spread and the excess bond premium in individual countries within the euro area and outside the euroarea, we find that only the core European countries have similar magnitudes for coefficients on the bond spreads. Other countries in the euro area have differences in the magnitude of coefficients from the core, as does the UK.

Our results imply that the careful selection of the European bonds used to construct the credit spread index, excluding those with embedded options and or illiquid secondary markets, delivers a robust indicator of financial market tightness that is distinct from tightness due to monetary policy measures or leading indicators of economic activity in Europe, confirming earlier results by Gilchrist *et al*. (2009a), Gilchrist and Zakrajšek (2012) and Faust *et al.* (2012) using data for the United States. This European bond spread provides information that is not measured in monetary tightness variables or economic leading indicators, and when we extract principal components from a large macroeconomic data set we continue to find that this spread retains its significance. The interpretation of the bond spreads is consistent with a 'balance sheet' channel previously supported by de Bondt (2004). The variation in the bond spread is mostly due to variation in the unpredictable part of the spread left over when default risk and bond characteristics a have been eliminated. This may reflect switches between 'search-for-yield' on riskier assets and 'flight-to-quality' due to 'portfolio shocks' (Heaton and Lucas, 1997; Bonaparte and Cooper, 2009), aversion to 'volatility shocks' (Fernandez-Villaverde *et al.* 2009) or 'risk premium shocks' (Kim, 2009), showing us when investors decide they are willing (unwilling) to hold corporate bonds during 'risk on' v. 'risk off' episodes. Therefore yield spreads may reflect asset allocation decisions of investors based on these considerations.

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Appendix (not for publication)

To demonstrate robustness we construct three alternative spread index measures, labelled Version L, R and W. The first modification, Version L, takes the logarithm of 1+EGZ Spread before taking the cross-sectional average:

$$S_{it}^{l} = \frac{1}{N_t}\sum \ln\left(1 + S_{jit[k]}\right)$$

The aim of this transformation is to dampen sharp spikes in the bond spread given its highly skewed distribution.

The second modification, Version R, rescales the spread by the risk free rate as follows:

$$S_{jit[k]}^{r} = \frac{y_{jit[k]} - y_{jit[k]}^{f}}{1 + y_{jit[k]}^{f}}$$

This transformation defines the bond spread as a pure function of default risk.

The third modification, Version W, weights the bond spreads at a given period of time within each country, where the weights represent the market value of the amount outstanding (deflated by CPI) of the respective bond issue. The weighted average bond spread index is defined as:

$$S_{it}^{w} = \frac{\sum\left(S_{jit[k]} * AOS_{jit[k]}\right)}{\sum AOS_{jit[k]}}$$

The weight attached to each bond spread in the index varies with the size of the respective issue, allowing bigger issues to account for a greater proportion of the index and potentially have a greater impact on our economic variables. The relationship between the three alternative EGZ spreads and the original EGZ spread is shown in Figure A1.

Table A1 reports the results for the log (L), re-scaled (R) and weighted (W) versions of the EGZ spread as a predictor of real GDP at the 1, 4 and 8 quarter horizon. There is the expected consistency between impact of the original measure on real activity and the L and R versions based on fixed effects estimates. For example, at the 4 quarter horizon a 100 basis point increase in the bond spread results in a 1.1 percentage point decline in the real GDP growth rate in L and R versions, which is identical to the estimate in Table 3. At other horizons there is a similar correspondence between the estimated coefficients. The estimate for the weighted version is different, however, since the response to a 100 basis point increase in the bond spread at the 4 quarter horizon results in a 1.5 percentage point decrease in the real GDP growth rate. The differences can be accounted for by the fact that the weighted measure of the EGZ spread is noticeably different to the other measures in the late 1990s and in the period after 2010 as seen in Figure 2. With these alternative measures the consumer confidence and the OECD composite leading indicator measure continues to have the positive impact on real GDP growth that we observed with the original spread, but economic sentiment is now insignificant at shorter horizons. The robustness of this result shows that the EGZ spread has additional predictive power over other forward-looking indicators, and it confirms the support for the financial accelerator model.

Comparing the alternative measures of the decomposed spread in Table A2, we find that the results for the log (L), re-scaled (R) and weighted (W) versions of the bond spread as a predictor of real GDP at the 1, 4 and 8 quarter horizons are similar. There is greater consistency between the original measure, the L and R versions than there is for the weighted version, as we found for the bond spread. In these regressions the OECD composite leading indicator continues to have the positive impact on real GDP growth that we observed previously and economic sentiment is again significant. We continue to show that the decomposed spread has predictive power even when other indicators are included in the regression, maintaining our support for the financial accelerator model.

Figure A1. The EGZ Bond Spread and Alternatives

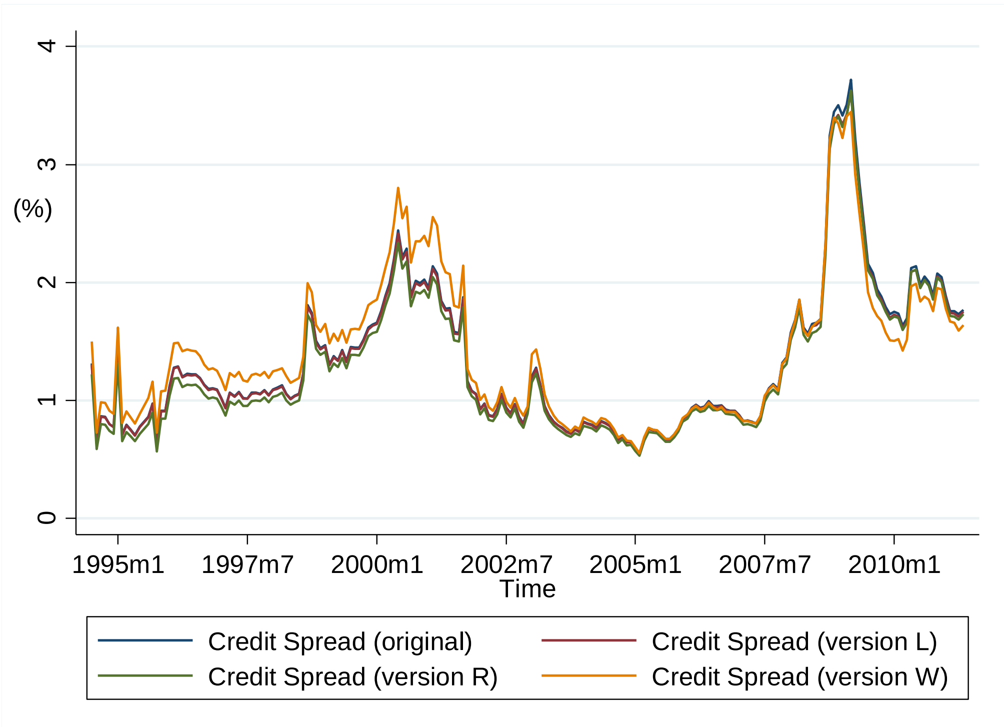

Table A1

Financial Indicator	Real GDP Growth								
	1 quarter			4 quarters			8 quarters		
	L	R	W	L	R	W	L	R	W
Term Spread	-0.433	-0.456	-0.380	-0.585	-0.615	-0.515	0.173	0.149	0.208
	(0.355)	(0.358)	(0.349)	(0.462)	(0.471)	(0.429)	(0.320)	(0.329)	(0.297)
Real Interest Rate	-0.173	-0.193	-0.124	-0.259	-0.290	-0.175	0.215	0.186	0.267
	(0.232)	(0.235)	(0.226)	(0.337)	(0.341)	(0.327)	(0.300)	(0.305)	(0.291)
Bond Spread	-1.030***	-0.993***	-1.253***	-1.171**	-1.092**	-1.543***	-1.382***	-1.311***	-1.603***
	(0.270)	(0.265)	(0.315)	(0.525)	(0.515)	(0.569)	(0.445)	(0.456)	(0.454)
Consumer Confidence	0.0659**	0.0665**	0.0569*	0.0909**	0.0925**	0.0764*	0.0495**	0.0503**	0.0399*
	(0.0289)	(0.0291)	(0.0297)	(0.0420)	(0.0425)	(0.0420)	(0.0221)	(0.0224)	(0.0219)
Economic Sentiment	0.0137	0.0141	0.0172	-0.132*	-0.129*	-0.133*	-0.176**	-0.175**	-0.172**
	(0.0380)	(0.0378)	(0.0384)	(0.0712)	(0.0712)	(0.0675)	(0.0680)	(0.0693)	(0.0663)
D4.CLI	0.261***	0.263***	0.252***	0.231***	0.232***	0.220***	0.209**	0.213**	0.198**
	(0.0790)	(0.0793)	(0.0789)	(0.0848)	(0.0858)	(0.0818)	(0.0944)	(0.0944)	(0.0970)
Observations	255	255	255	231	231	231	199	199	199
R-squared	0.661	0.659	0.668	0.417	0.411	0.440	0.327	0.319	0.343
CD p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FE/RE	0.002	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Robust Hausman	0.113	0.125	0.024	0.000	0.000	0.000	0.201	0.148	0.133

Notes: Sample period: July 1994 – May 2011. The columns headed L, R and W stand for log (L), re-scaled (R) and weighted (W) versions of the EGZ spread. Within R-squared reported for FE models. The CD p-value represents the Cross-sectional Dependence test p-value. The FE/RE represents the p-value for the significance of fixed-effects in FE models. Newey-West or Driscoll-Kraay standard errors are reported in parentheses as per the CD p-value. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A2.

Financial Indicator	Real GDP Growth								
	1 quarter			4 quarters			8 quarters		
	L	R	W	L	R	W	L	R	W
Term Spread	-0.812	-0.847	-0.894*	-0.941	-0.997*	-1.001*	-0.00331	-0.0510	-0.0442
	(0.582)	(0.589)	(0.533)	(0.564)	(0.579)	(0.520)	(0.356)	(0.367)	(0.345)
Real Interest Rate	-0.0323	-0.0663	-0.0979	-0.208	-0.259	-0.243	0.333	0.285	0.313
	(0.286)	(0.291)	(0.293)	(0.393)	(0.402)	(0.398)	(0.348)	(0.356)	(0.352)
Predicted Spread	0.0941	0.108	1.434*	0.0389	0.0618	1.482	-0.310	-0.286	1.205
	(0.276)	(0.276)	(0.750)	(0.474)	(0.479)	(0.908)	(0.609)	(0.620)	(1.109)
EBP	-2.039***	-1.984***	-2.587***	-1.714***	-1.598***	-2.312***	-1.618***	-1.508***	-2.070***
	(0.369)	(0.359)	(0.438)	(0.520)	(0.512)	(0.643)	(0.369)	(0.386)	(0.430)
Consumer Confidence	0.0686*	0.0689*	0.0666**	0.0710*	0.0729*	0.0646*	0.0251	0.0266	0.0152
	(0.0356)	(0.0361)	(0.0320)	(0.0370)	(0.0384)	(0.0372)	(0.0206)	(0.0213)	(0.0179)
Economic Sentiment	-0.0744**	-0.0731*	-0.0685*	-0.169**	-0.167**	-0.165**	-0.186***	-0.183**	-0.183***
	(0.0370)	(0.0377)	(0.0356)	(0.0693)	(0.0700)	(0.0665)	(0.0693)	(0.0708)	(0.0651)
D4.CLI	0.304***	0.305***	0.309***	0.254***	0.257***	0.257***	0.216**	0.221**	0.255**
	(0.0814)	(0.0824)	(0.0807)	(0.0828)	(0.0850)	(0.0814)	(0.104)	(0.105)	(0.108)
Observations	185	185	185	185	185	185	157	157	157
R-squared	0.739	0.737	0.741	0.493	0.483	0.515	0.381	0.366	0.403
CD p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FE/RE	0.033	0.031	0.022	0.015	0.016	0.004	0.003	0.003	0.000
Robust Hausman	0.000	0.000	0.015	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Sample period: January 1996 – August 2010. The columns headed L, R and W stand for log (L), re-scaled (R) and weighted (W) versions of the EGZ spread. Within R-squared reported for FE models. The CD p-value represents the Cross-sectional Dependence test p-value. The FE/RE represents the p-value for the significance of fixed-effects in FE models. Newey-West or Driscoll-Kraay standard errors are reported in parentheses as per the CD p-value. *** p<0.01, ** p<0.05, * p<0.1

Figure 1. The EGZ Spread Index and the Bloomberg Z-spread Index

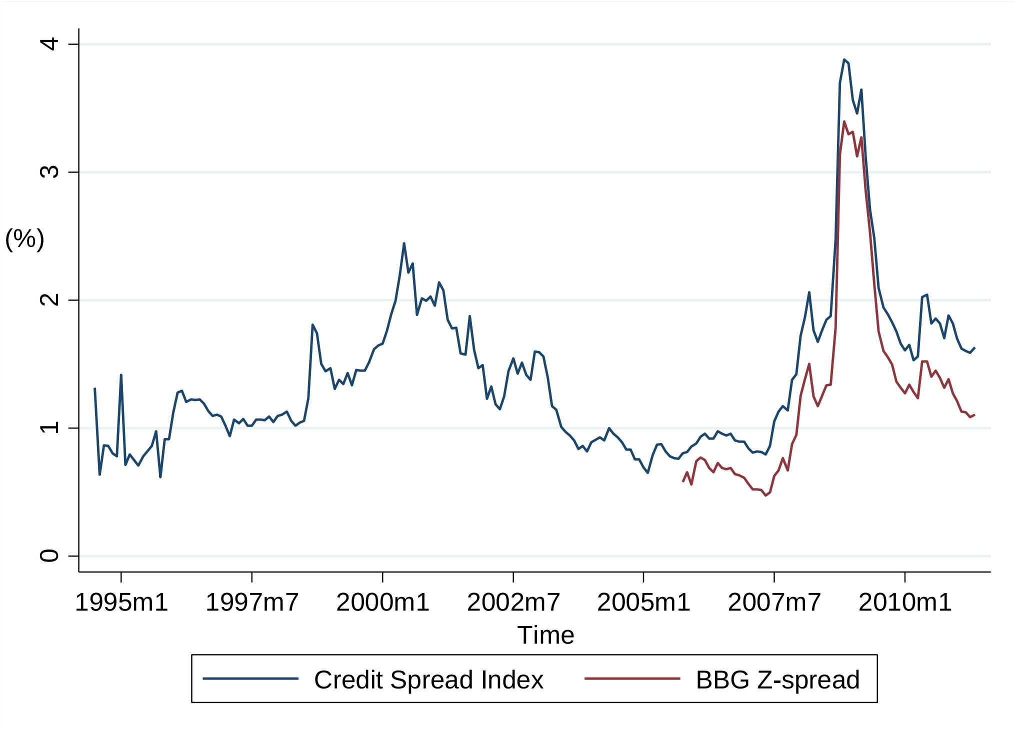

Figure 2. The EGZ Spread and the Bloom's measure of European Policy Uncertainty.

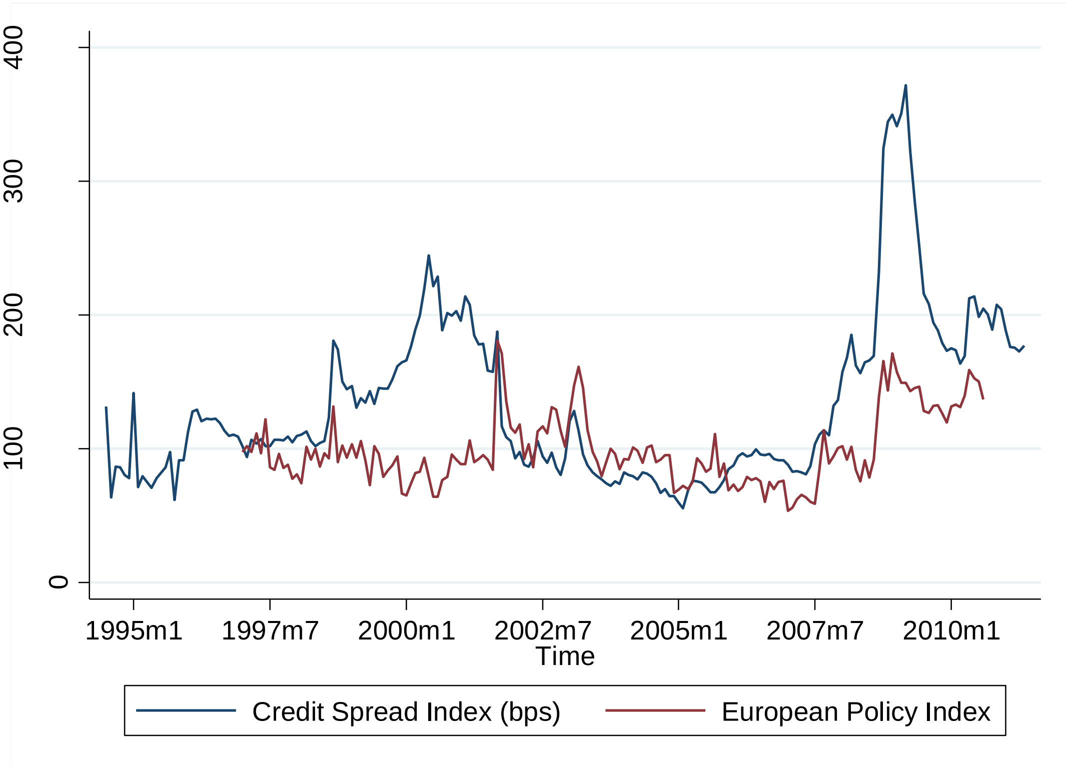

Figure 3. The Actual and Predicted EGZ Bond Spread

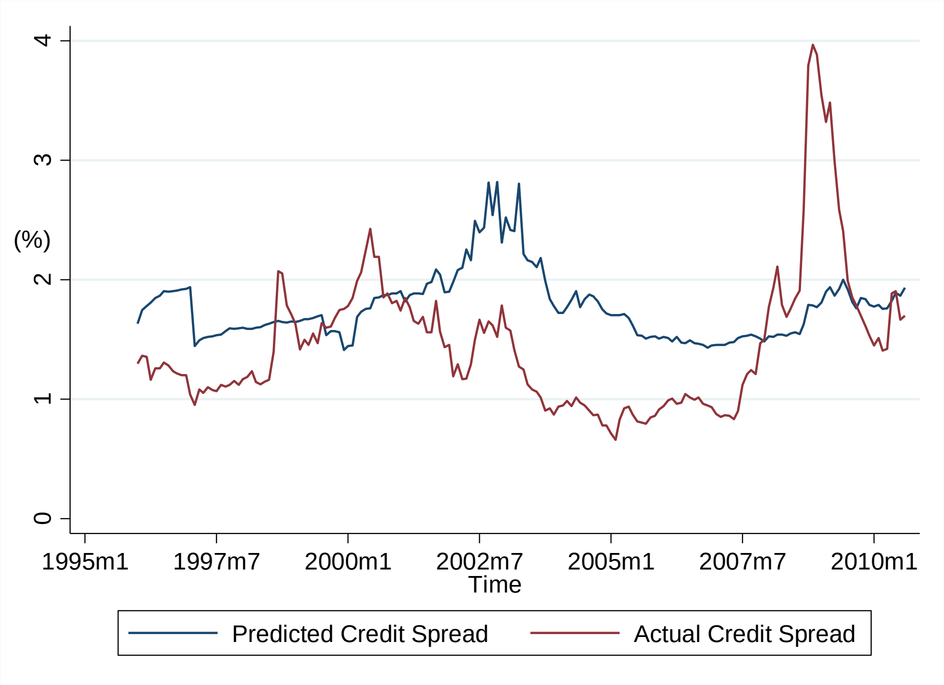

Figure 4. The EGZ Excess Bond Premium

Table 2.

Financial Indicator	Industrial Production			Unemployment Rate			Employment			Real GDP		
	Forecast Horizon: 12 months / 4 quarters											
	Panel 1			Panel 2			Panel 3			Panel 4		
	OLS1	FE1	RE1	OLS2	FE2	RE2	OLS3	FE3	RE3	OLS4	FE4	RE4
Term Spread	1.785	1.472	1.474**	-1.561	-1.781	-1.696	-0.377**	-0.326**	-0.352	0.242	0.0433	0.11
	(1.374)	(0.976)	(0.661)	(2.257)	(1.831)	(3.481)	(0.168)	(0.132)	(0.292)	(0.401)	(0.315)	(0.317)
Real Interest Rate	-0.936	-1.632*	-1.581	-0.692	-0.247	-0.27	-0.133	-0.161	-0.157	0.0895	-0.311	-0.138
	(0.761)	(0.876)	(1.697)	(1.406)	(1.415)	(3.622)	(0.113)	(0.139)	(0.248)	(0.288)	(0.292)	(0.540)
Bond Spread	-2.104	-2.822**	-2.708***	6.080**	7.826***	7.515***	-0.853***	-1.064***	-0.981**	-1.218**	-1.568***	-1.359***
	(1.360)	(1.343)	(0.533)	(2.608)	(2.137)	(2.642)	(0.191)	(0.159)	(0.393)	(0.492)	(0.421)	(0.310)
Observations	792	792	792	792	792	792	258	258	258	263	263	263
R-squared	0.203	0.268	0.199	0.104	0.160	0.103	0.291	0.361	0.289	0.176	0.289	0.168
CD p-value	0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000	
FE/RE		0.000	0.000		0.000	0.000		0.000	0.000		0.000	0.000
Robust Hausman			0.109			0.789			0.000			0.000

Notes: Sample period: July 1994 – May 2011. R-squared reported for OLS models, Within R-squared reported for FE models and Overall R-squared reported for RE models. The CD p-value represents the Cross-sectional Dependence test p-value. The FE/RE represents the p-value for the significance of fixed-effects in FE models and the p-value for the Breusch and Pagan Lagrangian multiplier test for random effects in RE models, respectively. Newey-West or Driscoll-Kraay standard errors are reported in parentheses for OLS and FE models as per the CD p-value, and Robust standard errors only are reported for the RE models. *** p<0.01, ** p<0.05, * p<0.1

Table 3.

Financial Indicator	1 quarter		4 quarters		8 quarters	
	FE1	FE2	FE3	FE4	FE5	FE6
Term Spread	-0.601	-0.441	-0.32	-0.597	0.551	0.166
	(0.372)	(0.356)	(0.469)	(0.468)	(0.483)	(0.326)
Real Interest Rate	-0.104	-0.178	-0.338	-0.272	-0.00841	0.203
	(0.229)	(0.234)	(0.344)	(0.340)	(0.267)	(0.304)
Bond Spread	-1.289***	-0.992***	-0.904**	-1.101**	-0.748**	-1.305***
	(0.230)	(0.258)	(0.380)	(0.508)	(0.365)	(0.442)
Consumer Confidence		0.0661**		0.0917**		0.0498**
		(0.029)		(0.042)		(0.022)
Economic Sentiment		0.0137		-0.130*		-0.175**
		(0.038)		(0.071)		(0.069)
D4.CLI	0.321***	0.261***	0.177***	0.231***	0.0703	0.211**
	(0.082)	(0.079)	(0.057)	(0.085)	(0.065)	(0.094)
Observations	255	255	231	231	199	199
R-squared	0.640	0.660	0.370	0.414	0.112	0.322
CD p-value	0.000	0.000	0.000	0.000	0.000	0.000
FE/RE	0.000	0.002	0.000	0.000	0.000	0.000
Robust Hausman	0.000	0.121	0.000	0.000	0.000	0.175

Real GDP Growth (dependent variable heading spanning all columns)

Notes: Sample period: July 1994 – May 2011. Within R-squared reported for FE models. The CD p-value represents the Cross-sectional Dependence test p-value. The FE/RE represents the p-value for the significance of fixed-effects in FE models. Newey-West or Driscoll-Kraay standard errors are reported in parentheses as per the CD p-value. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Bond Spreads and Expected Default Frequency

	OLS1	OLS2
VARIABLE	**Est.**	**Est.**
	(S.E.)	**(S.E.)**
Ln(1+*EDF*)	0.854***	1.299***
	(0.299)	(0.316)
[Ln(1+*EDF*)]^2		-5.648***
		(1.886)
Ln(1+*CPN*)	0.139***	0.130***
	(0.031)	(0.031)
Ln(*DUR*)	-0.00233	-0.00201
	(0.002)	(0.001)
Ln(*AOS*)	-0.00076	-0.00073
	(0.000)	(0.001)
Ln(*AGE*)	0.000598***	0.000606***
	(0.000)	(0.000)
Observations	7,639	7,639
R-squared	0.459	0.470
Industry Effects	0.000	0.000
Bond Rating Effects	0.000	0.000

Notes: Sample period: January 1996 – August 2010
Standard errors clustered at country and time dimensions
*** p<0.01, ** p<0.05, * p<0.1

Table 5.

Financial Indicator	Real GDP Growth					
	1 quarter		4 quarters		8 quarters	
	FE1	FE2	FE3	FE4	FE5	FE6
Term Spread	-0.632	-0.822	-0.342	-0.969*	0.55	-0.0306
	(0.569)	(0.585)	(0.598)	(0.573)	(0.557)	(0.365)
Real Interest Rate	-0.0106	-0.0478	-0.254	-0.236	0.125	0.304
	(0.290)	(0.287)	(0.427)	(0.399)	(0.366)	(0.354)
Predicted Spread	0.185	0.108	0.296	0.0723	-0.0936	-0.256
	(0.291)	(0.270)	(0.371)	(0.460)	(0.549)	(0.600)
EBP	-1.942***	-1.946***	-1.227***	-1.593***	-0.919***	-1.497***
	(0.319)	(0.347)	(0.433)	(0.504)	(0.312)	(0.374)
Consumer Confidence		0.0687*		0.0720*		0.0257
		(0.036)		(0.038)		(0.021)
Economic Sentiment		-0.0725*		-0.167**		-0.183**
		(0.037)		(0.069)		(0.070)
D4.CLI	0.278***	0.303***	0.150***	0.254***	0.0368	0.218**
	(0.072)	(0.082)	(0.056)	(0.084)	(0.067)	(0.104)
Observations	185	185	185	185	157	157
R-squared	0.728	0.739	0.409	0.488	0.162	0.372
CD p-value	0.000	0.000	0.000	0.000	0.000	0.000
FE/RE	0.000	0.028	0.000	0.015	0.000	0.003
Robust Hausman	0.033	0.000	0.020	0.000	0.033	0.000

Notes: Sample period: January 1996 – August 2010. Within R-squared reported for FE models. The CD p-value represents the Cross-sectional Dependence test p-value. The FE/RE represents the p-value for the significance of fixed-effects in FE models. Newey-West or Driscoll-Kraay standard errors are reported in

Table 6.

Real GDP Growth						
Financial Indicator	**1 quarter**		**4 quarters**		**8 quarters**	
	FE1	**FE2**	**FE3**	**FE4**	**FE5**	**FE6**
Term Spread	-0.617	-0.460	-0.267	-0.780*	0.626	0.0211
	(0.388)	(0.376)	(0.463)	(0.462)	(0.461)	(0.235)
Real Interest Rate	-0.0939	-0.151	-0.272	-0.149	0.0668	0.378
	(0.232)	(0.235)	(0.347)	(0.328)	(0.238)	(0.258)
CS*AT	-0.467	-0.242	0.174	-0.179	0.167	-0.474
	(0.363)	(0.381)	(0.371)	(0.371)	(0.336)	(0.322)
CS*BE	-1.170**	-0.965*	-0.988	-1.876*	-1.038	-2.288***
	(0.570)	(0.538)	(0.790)	(0.995)	(0.795)	(0.628)
CS*FR	-1.104***	-0.851***	-0.898**	-1.365***	-0.775**	-1.587***
	(0.174)	(0.242)	(0.401)	(0.469)	(0.310)	(0.253)
CS*DE	-0.958	-0.929	-0.401	-0.280	-0.407	-0.0283
	(0.575)	(0.559)	(0.472)	(0.473)	(0.643)	(0.476)
CS*UK	-2.319***	-1.872***	-1.668**	-2.485***	-1.176*	-2.568***
	(0.493)	(0.561)	(0.672)	(0.772)	(0.625)	(0.491)
CS*IT	-1.870***	-1.735***	-1.401**	-2.274***	-1.131**	-2.324***
	(0.505)	(0.585)	(0.529)	(0.744)	(0.564)	(0.438)
CS*NL	-1.773***	-1.457***	-1.653***	-1.897***	-1.399**	-1.919***
	(0.406)	(0.415)	(0.607)	(0.589)	(0.598)	(0.296)
CS*SP	-1.365***	-0.995*	-1.980***	-2.256***	-1.899***	-2.764***
	(0.475)	(0.577)	(0.599)	(0.781)	(0.680)	(0.782)
Consumer Confidence		0.0642**		0.0795*		0.0342
		(0.0265)		(0.0426)		(0.0205)
Economic Sentiment		0.00659		-0.178**		-0.237***
		(0.0456)		(0.0766)		(0.0597)
D4.CLI	0.319***	0.265***	0.169***	0.278***	0.0551	0.319***
	(0.0816)	(0.0816)	(0.0580)	(0.0868)	(0.0834)	(0.106)
Observations	255	255	231	231	199	199
R-squared	0.666	0.681	0.434	0.501	0.267	0.501
CD p-value	0.000	0.000	0.000	0.000	0.000	0.000
FE/RE	0.008	0.062	0.001	0.000	0.000	0.000
F-test	0.000	0.003	0.000	0.000	0.000	0.000
F-test (excl. UK)	0.002	0.010	0.000	0.000	0.000	0.000
F-test (FR, DE, NL)	0.187	0.208	0.003	0.000	0.000	0.000
Robust Hausman	0.000	0.103	0.000	0.000	0.000	0.000

Notes: Sample period: July 1994 – May 2011. Within R-squared reported for FE models. The CD p-value represents the Cross-sectional Dependence test p-value. The FE/RE represents the p-value for the significance of fixed-effects in FE models. Newey-West or Driscoll-Kraay standard errors are reported in parentheses as per the CD p-value. *** p<0.01, ** p<0.05, * p<0.1

Table 7.

Real GDP Growth						
Financial Indicator	**1 quarter**		**4 quarters**		**8 quarters**	
	FE1	**FE2**	**FE3**	**FE4**	**FE5**	**FE6**
Term Spread	-0.572	-0.748*	-0.126	-0.751*	0.599	-0.0726
	(0.401)	(0.417)	(0.424)	(0.439)	(0.461)	(0.238)
Real Interest Rate	0.0173	0.0531	-0.111	0.0614	0.153	0.513**
	(0.196)	(0.184)	(0.312)	(0.275)	(0.247)	(0.253)
Predicted Spread	-0.672	-0.721*	0.0633	-0.339	-0.153	-0.578**
	(0.407)	(0.417)	(0.294)	(0.401)	(0.426)	(0.269)
EBP*AT	-2.343***	-2.220***	-1.874***	-2.112***	-1.192	-1.078*
	(0.762)	(0.833)	(0.590)	(0.666)	(0.953)	(0.605)
EBP*BE	-2.059*	-2.658**	-1.646*	-3.173**	-1.124	-3.051***
	(1.156)	(1.247)	(0.925)	(1.256)	(0.961)	(0.752)
EBP*FR	-1.704***	-1.854***	-1.307***	-2.012***	-1.042**	-1.987***
	(0.223)	(0.277)	(0.470)	(0.520)	(0.436)	(0.310)
EBP*DE	-1.519***	-1.350**	-0.662*	-0.443	-0.124	0.275
	(0.547)	(0.643)	(0.374)	(0.449)	(0.534)	(0.533)
EBP*UK	-2.278***	-2.420***	-1.523***	-2.465***	-1.087***	-2.466***
	(0.481)	(0.526)	(0.550)	(0.690)	(0.362)	(0.353)
EBP*IT	-2.230***	-2.679***	-1.581***	-2.574***	-0.869*	-2.056***
	(0.426)	(0.495)	(0.497)	(0.657)	(0.487)	(0.369)
EBP*NL	-1.841***	-1.806***	-1.733***	-1.983***	-1.322***	-1.700***
	(0.467)	(0.445)	(0.478)	(0.417)	(0.474)	(0.152)
Consumer Confidence		0.0856**		0.0850**		0.0414**
		(0.0357)		(0.0370)		(0.0182)
Economic Sentiment		-0.0998**		-0.212**		-0.258***
		(0.0455)		(0.0825)		(0.0646)
D4.CLI	0.275***	0.311***	0.142**	0.278***	0.0587	0.338***
	(0.0665)	(0.0811)	(0.0545)	(0.0930)	(0.0858)	(0.126)
Observations	200	200	200	200	172	172
R-squared	0.720	0.736	0.451	0.555	0.230	0.548
CD p-value	0.000	0.000	0.000	0.000	0.000	0.000
FE/RE	0.000	0.202	0.000	0.006	0.000	0.001
F-test	0.041	0.062	0.000	0.001	0.000	0.000
F-test (excl. UK)	0.047	0.042	0.000	0.002	0.000	0.000
F-test (FR, DE, NL)	0.889	0.726	0.002	0.017	0.000	0.000
Robust Hausman	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Sample period: January 1996 – August 2010. Within R-squared reported for FE models. The CD p-value represents the Cross-sectional Dependence test p-value. The FE/RE represents the p-value for the significance of fixed-effects in FE models. Newey-West or Driscoll-Kraay standard errors are reported in parentheses as per the CD p-value. *** p<0.01, ** p<0.05, * p<0.1

Table 8.

Real GDP	1-quarter			4-quarter			8-quarter		
	FE1	**FE2**	**FE3**	**FE1**	**FE2**	**FE3**	**FE1**	**FE2**	**FE3**
Credit Spread	-2.363***	-2.475***	-2.579***	-1.577***	-1.679***	-1.872***	-0.899***	-1.075***	-1.077***
	(0.504)	(0.519)	(0.587)	(0.277)	(0.291)	(0.446)	(0.160)	(0.135)	(0.131)
IR	-0.559	-0.549*	-0.692*	-1.054***	-1.025***	-1.201***	-1.603***	-1.569***	-1.577***
	(0.373)	(0.290)	(0.400)	(0.302)	(0.290)	(0.427)	(0.189)	(0.229)	(0.213)
ER	-0.414	-0.129	-0.163	-0.344**	-0.0676	-0.0829	-0.364***	-0.134***	-0.125***
	(0.319)	(0.206)	(0.193)	(0.154)	(0.101)	(0.109)	(0.093)	(0.048)	(0.042)
M	0.0262	0.0734	-0.00839	0.0867	0.195**	0.094	0.0336	0.113***	0.107**
	(0.136)	(0.138)	(0.145)	(0.100)	(0.095)	(0.098)	(0.047)	(0.040)	(0.048)
P	0.561**	0.351	0.291	-0.118	-0.182	-0.29	-0.209**	-0.212*	-0.212**
	(0.224)	(0.227)	(0.278)	(0.191)	(0.222)	(0.309)	(0.078)	(0.112)	(0.094)
SPI	0.725	0.566		1.016**	0.722**		0.179	0.0683	
	(0.458)	(0.385)		(0.375)	(0.340)		(0.138)	(0.159)	
NT	-0.17	-0.0857		-0.0327	0.0441		-0.0769	-0.0141	
	(0.136)	(0.112)		(0.148)	(0.097)		(0.088)	(0.069)	
RT	-0.171	0.045		-0.0254	0.157		-0.118	-0.0611	
	(0.171)	(0.142)		(0.124)	(0.140)		(0.084)	(0.108)	
CPI exfe	-0.0375			-0.194*			0.0489		
	(0.188)			(0.101)			(0.062)		
M1	-0.0976			0.165			0.137*		
	(0.100)			(0.136)			(0.079)		
Observations	172	244	244	160	226	226	136	194	194
R-squared	0.577	0.550	0.526	0.615	0.566	0.508	0.713	0.639	0.638
CD p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FE/RE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Robust Hausman	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 9.

Real GDP	1-quarter			4-quarter			8-quarter		
	FE1	**FE2**	**FE3**	**FE1**	**FE2**	**FE3**	**FE1**	**FE2**	**FE3**
Predicted Spread	-1.573***	-1.561***	-1.601***	-0.724***	-0.523**	-0.610*	-0.419***	-0.378**	-0.359***
	(0.415)	(0.368)	(0.369)	(0.243)	(0.248)	(0.304)	(0.102)	(0.150)	(0.124)
EBP	-3.070***	-3.310***	-3.423***	-1.926***	-2.187***	-2.362***	-0.846***	-1.220***	-1.193***
	(0.490)	(0.481)	(0.551)	(0.252)	(0.261)	(0.392)	(0.156)	(0.115)	(0.129)
IR	-0.436	-0.463	-0.534*	-1.038***	-0.915***	-1.053***	-1.535***	-1.448***	-1.440***
	(0.379)	(0.296)	(0.313)	(0.251)	(0.223)	(0.319)	(0.223)	(0.275)	(0.264)
ER	-0.299	-0.0722	-0.0736	-0.337***	-0.0478	-0.0754	-0.380***	-0.114*	-0.117**
	(0.310)	(0.193)	(0.185)	(0.114)	(0.094)	(0.095)	(0.072)	(0.065)	(0.052)
M	-0.174	-0.12	-0.178	-0.165**	-0.0297	-0.107	-0.105*	0.017	0.035
	(0.146)	(0.139)	(0.148)	(0.072)	(0.078)	(0.084)	(0.056)	(0.045)	(0.066)
P	0.365	0.142	0.0889	-0.394*	-0.379	-0.503	-0.291***	-0.275**	-0.265***
	(0.253)	(0.229)	(0.270)	(0.219)	(0.245)	(0.330)	(0.064)	(0.111)	(0.077)
SPI	0.416	0.3		0.805**	0.531*		0.0433	-0.0345	
	(0.478)	(0.341)		(0.325)	(0.272)		(0.135)	(0.180)	
NT	-0.0847	-0.0379		0.0773	0.167**		-0.0707	0.0517	
	(0.074)	(0.077)		(0.120)	(0.069)		(0.100)	(0.079)	
RT	-0.13	0.0827		-0.0248	0.207		-0.171*	-0.044	
	(0.171)	(0.161)		(0.151)	(0.183)		(0.096)	(0.146)	
CPI exfe	-0.0868			-0.229*			-0.0262		
	(0.175)			(0.122)			(0.067)		
M1	0.00632			0.305**			0.223***		
	(0.114)			(0.126)			(0.076)		
Observations	124	189	189	124	189	189	104	161	161
R-squared	0.650	0.657	0.650	0.702	0.647	0.609	0.726	0.638	0.637
CD p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FE/RE	0.041	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000
Robust Hausman	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000