Credit 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 straight 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 credit 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 and other leading indicator variables. Our results are consistent at different forecast horizons and are robust to different measures of the credit spreads. When we compare the predictive ability of the credit 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 credit spreads. Other countries in the euro area, and the UK, do not have similar predictive ability in the credit spreads.

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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. Despite considerable loosening of monetary policy as the authorities cut short term interest rates and engaged in quantitative easing, rates for borrowers have not necessarily fallen. Policy measures have lowered both short and long term interest rates, but the economic outlook has deteriorated, and markets have revised upwards the risk premiums they require to lend to businesses since 2007, and especially post-Lehman. The net effect on the credit spread is a combination of all three factors, so is it possible to disentangle these effects and connect them to measures of real activity? Moreover, if we split the credit spread into the predictable part and the unpredictable part, can we attribute the predictive ability over real activity to each part?

Previous literature by Gertler and Lown (1999) and Chan-Lau and Ivascenko (2001), has shown a tendency for bond spreads to explain real activity, and this was extended to high yield bonds by Mody and Taylor (2004) and King at el. (2007) for the United States. At about the same time early attempts were made by Davis and Fagan (1997) and De Bondt (2004) to undertake similar exercises for Europe. But the spreads that performed well in the 1980s did not perform as well in later decades: for example the Commercial Paper-Treasury Bill spread (Paper-Bill spread) and the bond spread (Baa-Aaa spread) ceased to predict as well in the 1990s as they had done previously. The most recent work on the relationship between bond spreads and real activity by Mueller (2009), Gilchrist *et al*. (2009), Gilchrist and Zakrajšek (2011) and Faust *et al*. (2011) has concentrated on careful selection of bonds to ensure the spread is not distorted by bonds with embedded options, or bonds that are illiquid. They also ensure that the maturity structure corresponds to business cycle frequencies, rather than the very short term. These papers find credit spreads predict future changes to real activity, but clearly the definition of the spreads and their measurement is critical to the findings of the literature.

In this paper we focus on the 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, the second and third largest bond markets, respectively, after the United States.[3] We take the Gilchrist and Zakrajšek (2011) approach to constructing credit spreads from individual corporate bond data obtained from Bloomberg, and use this to predict real activity such as industrial production, employment, unemployment and real GDP growth. At the same time we include measures of monetary policy tightness, such as the term spread and the real interest rate, as well as leading indicators of economic performance, such as consumer confidence, economic sentiment and the OECD composite leading indicator for each country. We then repeat the exercise

[3] Source: Bank for International Settlements, Quarterly Review, March 2012.

after purging individual bond spreads of bond-specific characteristics (e.g. duration, coupon, amount outstanding, age) and firm-specific characteristics (estimated distance to default) to derive an excess bond premium.

This allows us to make several contributions to the literature on the relationship between real activity and financial market tightness in Europe. First, we can evaluate the importance of credit spreads, and excess bond premiums extracted by removing the predictable part of the spread, in predicting real activity at the country level. We can then compare these indicators versus measures of monetary policy tightness and signals from leading indicators of economic performance, to disentangle the contributions of tightness in credit markets from other influences when predicting real activity. We do this at different forecast horizons to determine the consistency of the predictions we observe. Second, since we construct a country-by-country level European version of the Gilchrist and Zakrajšek spread (hereafter the EGZ spread), we can compare the predictive ability of the credit spread and the excess bond premium in individual countries within the euro area and outside the euroarea. Third, we make use of three alternative measures based on unweighted and value-weighted averages of individual bond spreads to determine the robustness of the credit spreads and excess bond premiums to the methods used in their construction.

We find that credit spreads and excess bond premiums, when used alongside monetary policy tightness indicators and leading indicators of economic performance, are highly significant for predicting the growth in the index of industrial production, employment growth, the unemployment rate and real GDP growth at horizons ranging from one quarter to two years ahead. These results are confirmed for individual countries in the euroarea and for the United Kingdom, and are robust to different measures of the credit spread. It is the unpredictable part associated with the excess bond premium that has greater influence on real activity compared to the predictable part of the credit spread. The implications of our results are that careful selection of the bonds used to construct the credit spreads, 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.

While monetary policy variables influence real activity through the interest rate and expectational channels, and leading indicators are direct measures of expectations, the credit spreads operate through the credit channel. The theoretical underpinning of this channel is the financial accelerator model of Gertler and Gilchrist (1994), Bernanke et al. (1999). A change in the firm's net worth will determine the costs the firm will face to obtain finance and ultimately its economic performance. In difficult times credit spreads will widen as lenders demand compensation given an increase in credit risk and the presence of financial market imperfections. This could be anticipated with the onset of a recession, and these should be detected by leading indicators that pick up expectations. But the financial accelerator model, *also* suggests credit spreads have an independent effect on future output because of their impact on investment and other real activity measures through the credit channel. Therefore, if credit spreads have predictive ability over real activity and retain this ability when other expectations measures are added, this confirms the influence of market tightness operating through the credit channel.

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 credit spreads and the decomposition of credit spreads into the predictable component and the excess bond premium. Section 6 discusses the findings and concludes.

2. Literature

There is a vast literature on the predictive ability of financial variables for real economic activity, much of which has been surveyed by Stock and Watson (2003). The methods used for this exercise have included dynamic factor models, Stock and Watson (2006), and models of the term structure, Ang et al (2006), Wright (2006), as well as leading indicator models.

Papers using information from corporate bond spreads over Treasuries, such as the Baa – Treasury spread, have attempted to deal with the fact that this spread contains information on the economic cycle from credit default risk, but also includes prepayment risks and liquidity risk, see Duca (1999). 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. There is good evidence that this risk varies over the business cycle, as does the other component we wish to remove from spreads, namely, liquidity risk. 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.* (1998)). 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).

Authors have sought to control for these effects by using different types of spreads that place greater emphasis on the components we wish to concentrate on. Gertler and Lown (1999) argue that the due to the greater risk of default in high-yield bonds, the spread has a relatively large component that is due to credit risks, and a smaller component that reflects prepayment or liquidity risk. They show that the spread has explanatory power over the GDP growth gap one quarter and one year ahead. Their results are robust to using two different risk-free benchmarks (the AAA corporate bonds and the 10-year government bond yield) and various other explanatory variables for both the entire sample between 1980Q1 and 1999Q1 and the subsample between 1985Q1 and 1999Q1. They conclude that the high-yield spread outperforms other leading financial spreads, including the Paper-Bill spread and the term spread, and the Federal Funds rate.

Chan-Lau and Ivaschenko (2001) argue it is not necessary to use high yield bonds. They suggest that prices of investment-grade bonds can accurately reflect economic fundamentals (such as expected return on investment) if they are correctly organised by maturity and bond rating. These authors split their bond indices according to maturity and rating class and use three different risk-free benchmarks (the US Treasury bond, Agency bond and AAA corporate bonds) to construct their spreads. Using Generalized Method of Moments (GMM) they find that the all-maturity and intermediate-maturity bond indices have significant predictive content while the long-maturity spreads lack explanatory power both in- and out-of-sample across rating classes and forecasting horizons. They also extract one main common factor affecting yield spreads using Principal Component Analysis (PCA) which accounts for 95% of the variation in yield spreads. They argue that PCA helps filter idiosyncrasies associated with particular credit classes and isolate the systematic component of risk and conclude the main factor contains significant information content for future economic activity.

Two further studies by Mody and Taylor (2004) and King *et al.* (2007) consider high yield bond spreads. Mody and Taylor (2004) use a quarterly index series of the yield on sub investment grade bonds between 1998Q1 and 2001Q4 and using standard time series regression analysis they confirm the information content of the high yield bond spread index. King *et al.* (2007) estimate logit models, univariate and bivariate models for the US from 1988 to 2007 for 54 different financial-market variables including AAA, AA, A, BBB, BB and B credit spreads, and the high yield credit spread at various maturities. They find that credit spreads on risky debt have been at least as informative as term spreads over the past two decades for predicting recessions, bivariate models fit the data much better than univariate models, both in and out of sample, and that the BMA model results in substantially better out-of-sample forecasts than simple averages.

Mueller (2009) uses quarterly data between 1992:Q2 and 2006:Q1 to regress future GDP growth on credit spreads of different rating classes and maturities. He finds that a seemingly arbitrary combination of credit spreads results in the best fit, suggesting the whole term structure of credit spreads across rating classes contains relevant information for real activity. He also decomposes the credit spread using Principal Component Analysis and concludes that one of the three latent factors (which are independent of the macro variables) termed as the credit factor, captures virtually all predictive power in corporate bond spreads. The credit factor is highly correlated with the Federal Reserve's Index of Tighter Loan Standards and can also be interpreted as a proxy for credit conditions.

Almost all of these studies have been 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, however. Davis and Fagan (1997) test for the predictive content of the credit quality spread (defined as the difference between private and government bonds) for three European countries individually (i.e. Denmark, Germany and the UK). They find a significant relationship only in Germany for both inflation and output growth, however, the out-of-sample forecasting results are weak. De Bondt (2004) offers the first empirical examination of the balance sheet channel in the euro area since the introduction of the single currency. He approximates 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. Their sample period is fairly short (January 1999 to June 2001), however, they use three different empirical methods (pairwise Granger causality tests, multivariate regression framework and bivariate unrestricted VARs). He distinguishes between two hypotheses: i) whether the balance sheet is operative and ii) whether it is macroeconomically relevant for measures of real activity.

The recent financial crisis has injected new interest into the literature on credit spreads and economic activity because economic activity has declined during a Great Recession and because credit 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 (2011) and Faust *et al*. (2011) 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. 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 (2011) seek to improve on the measurement of credit spreads, which have previously taken a top down approach, and have been unable to select individual bonds.

Gilchrist, Yankov and Zakrajsek (2009) construct a credit 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 credit-quality spectrum, a result also documented by Mueller (2009). They further assess the impact on the macroeconomy of movements in the credit spread in a structural VAR framework. They conclude that unexpected increases in the bond spreads cause large and persistent contractions in economic activity. Such credit market shocks explain 30% of the variance in economic activity at two- to four-year horizons.

Faust et al. (2011) adopts a similar method to Gilchrist, Yankov and Zakrajšek (2009), Gilchrist and Zakrajšek (2011), but includes bonds issued by financial firms as well as non-financial firms in their sample. After constructing the credit 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 credit 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 credit 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 credit spreads seems to improve forecast accuracy even in the 2007-2009 period.

3. Data Sources and Characteristics

We employ the same bottom-up approach guided by Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2011) to construct a country level credit 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 credit 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 (2011). 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 credit 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 credit 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 (2011) 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 credit 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 (2011) concluded that these spreads provide limited additional explanatory power in their results for US data when they include their credit 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 credit risk measure for the bond issuers in our sample[4]. The Moody's dataset

[4] 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 credit risk measure. The EDF measure is compiled using Moody's default database and leverages market data,

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 (2011), 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 (2011), we ensured 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, 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 credit 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.

industry, volatility, financial statement data, and historical default information in a proprietary financial model.

The credit spread index at the country-level in period t is then calculated as the arithmetic (or cross-sectional) average of all credit 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.

For 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 credit 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 credit 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 credit 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 2.

Explanatory variables used with our constructed EGZ Spreads to explain real activity include the term spread, the real interest rate, consumer confidence, and economic sentiment. 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 behaviour, data quality, timeliness and availability.

3.2 Descriptive Statistics

Table 1 reports there are 19574 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 (2011), 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.

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
Credit 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 credit spread of less than 5 bps and 67 observations (12 bonds) that have a term to maturity higher than 30 years. The credit spreads for these observations is however within the range of the full bonds sample and have therefore been included.

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 credit quality in our sample[5]. Compared to the US sample of bonds of Gilchrist and Zakrajšek (2011), 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 credit spread, and once averaged the credit spread index in Europe has a mean of 140.3 basis points above the risk-free rate.

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

In terms of default risk as measured by the S&P credit ratings our sample spans almost the entire spectrum of credit 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 credit 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 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 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 credit 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 credit 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 credit 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 credit spread exhibits negative correlations with industrial production, employment stock and real GDP growth and positive correlation with unemployment rate. The correlation between the credit 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 credit spread index and the term spread is 0.3.

4. Methodological Issues

To assess the predictive ability of credit spreads we use the forecasting specification used by Gilchrist and Zakrajšek (2011) in which the contemporaneous value of the credit spread is used to forecast the change in real economic activity over the following h periods. The forecasting specification is:

$$\Delta^h Y_{it+h} = \alpha + \beta * S_{it} + \sum_{k=1}^{4} \gamma_k * X_{itk} + u_i + e_{it+h}$$

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.[6] 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 credit 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 the coefficients to be estimated.

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 (2011) 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 and economic sentiment in our regressions to measure forward looking indicators of real activity.

We are able to decompose our credit spreads into the predicted component and the excess bond premium, which measures the element that compensates the investor for the taxation on corporate bonds, the risk of default and the required liquidity premium.

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[6] Following Gilchrist and Zakrajšek (2011), 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).

4.1 The EBP and the decomposition

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.

Our empirical methodology follows the lines of GZ in that the log of the credit spread on bond *k* issued by firm *j* in country *i* at time *t*, ln $S_{jit}[k]$, is assumed to be 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:

$$\ln\left(1 + S_{jit}[k]\right) = \alpha_i + \beta_i * \ln\left(1 + EDF_{jit}\right) + \gamma_i * \ln\left(Z_{jit}[k]\right) + \varepsilon_{jit}[k]$$

The choice of the explanatory variables is guided by GZ (2011) and King and Khang (2005). The vector of bond-specific characteristics is aimed at capturing 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, $AGE_{jit}[k]$.

Taking logs of the credit 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 credit 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 use the following transformation ln(1 + variable). In this case, the percentage change interpretations are closely preserved and it is acceptable to interpret the estimates as if the variable were ln(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 SEs are equivalent to clustering on the larger category. The regression also includes industry and credit 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. Credit 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 credit spread for bond k of firm j in country i at time t as follows:

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

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 credit 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:

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

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:

$$\hat{S}_{it} = \frac{1}{N_t}\sum_{j}\sum_{k}\hat{S}_{jit}[k]$$

And

$$EBP_{it} = \frac{1}{N_t}\sum_{j}\sum_{k}EBP_{jit}[k]$$

Our approach in constructing the EBP and the predicted spread differs slightly from GZ. While GZ define the EBP as the difference between the averaged credit 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.

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. random. 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 then 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 GZ Credit Spread

Table 2 determines the predictive ability of credit spreads for four different real activity measures – industrial production, the unemployment rate, the growth in employment, and real GDP – at the 12 month/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 credit 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 credit spread rises, and unemployment rate rises. The impact of the credit 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 (2011) we find that all four real activity measures in European economies show similar directional changes in the credit 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 credit 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 credit 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 credit 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 credit spreads have an independent effect on future output because of their impact on investment. Therefore, if our credit spread variable remains significant when we add the other leading indicator variables, we have confirmation that the credit spread influences real activity through the financial accelerator channel. This is indeed the case, since in every column in Table 3 the coefficient on the EGZ credit 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 credit 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 credit 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 credit spread through the financial accelerator channel.

We now check for robustness of our results to the construction of the EGZ Spread. Table 4 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 credit 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 credit 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.

5.2 Prediction with the Excess Bond Premium

We now decompose the credit spread of bond k issued by firm i in month t, into the predicted spread and the excess bond premium. Table 5 reports the results of the regression of the credit 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 credit 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 as Gilchrist and Zakrajšek (2011) have done. Therefore our models are 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 5, 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. Other variables are 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 5 (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. The fitted equation in Table 5 (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 credit spread and the EBP series which constitutes great evidence that the EBP is actually the source for most of the credit 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.

The EBP series is very similar to the US premium calculated by Gilchrist and Zakrajšek (2011). 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.

Table 6 evaluates the prediction of the real GDP growth rate using the decomposed credit 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 credit 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 (2011), 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.[7] The result is entirely consistent with the findings of Gilchrist and Zakrajšek (2011) for US data, who find that the predicted spread had no forecasting power from the mid 1980s onwards, but the EBP is 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.

Comparing the alternative measures of the decomposed spread in Table 7, we find that the results for the log (L), re-scaled (R) and weighted (W) versions of the credit 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 credit 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.

The purpose of Tables 8 and 9 is to compare the forecasting power of the credit spread and the decomposition into predicted credit spread and excess bond premium on the real GDP growth across countries. We observe in Table 8 that the credit spread interacted with the country dummies, has a coefficient that is significant and negatively signed for all countries except Germany and Austria. There is a high degree of consistency in the forecasting power at different horizons for each country. However, when we test for equality of coefficients on the credit 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 credit spreads are equal across these countries. Very similar results are obtained in Table 9, but here there is

[7] 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.

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.

6. Conclusions

In this paper we examine the relationship between real activity and financial market tightness in Europe. We evaluate the importance of credit 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 credit 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 credit spreads. When we compare the predictive ability of the credit 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 credit spreads. Other countries in the euro area, and the UK, do not have similar predictive ability in the credit spreads.

Our results imply that the careful selection of the bonds used to construct the credit spreads, 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. This spread provides information that is not measured in monetary tightness variables or economic leading indicators. For this reason, we argue, our results provide additional corroboration for the financial accelerator theory.

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Appendix

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

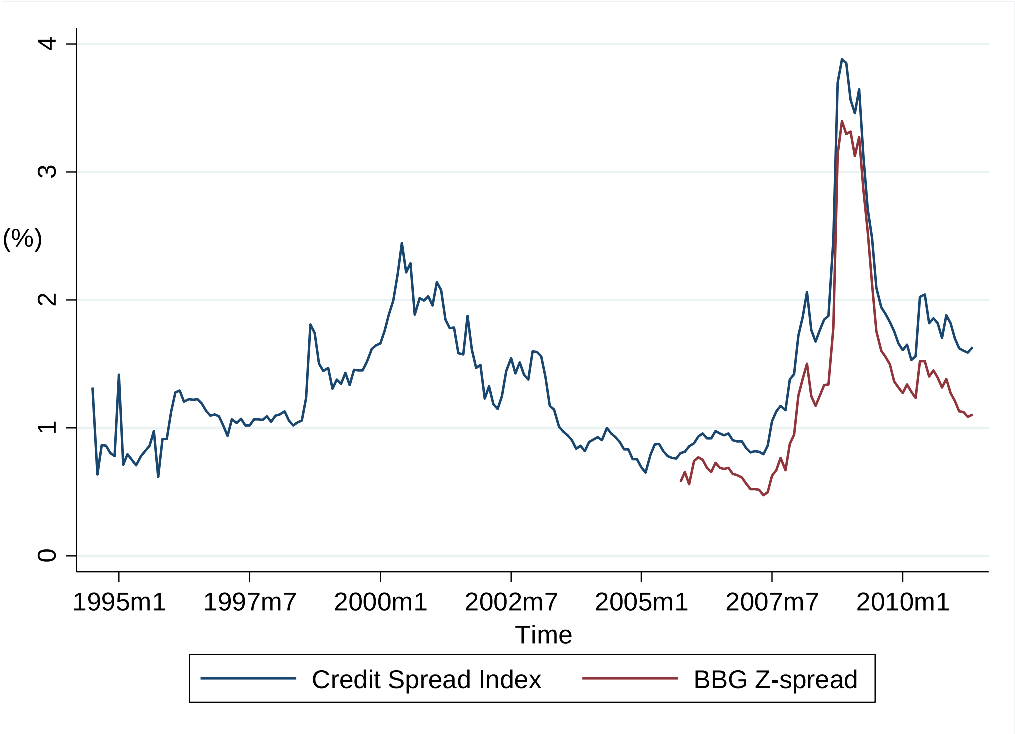

Figure 2. The EGZ Credit Spread and Alternatives

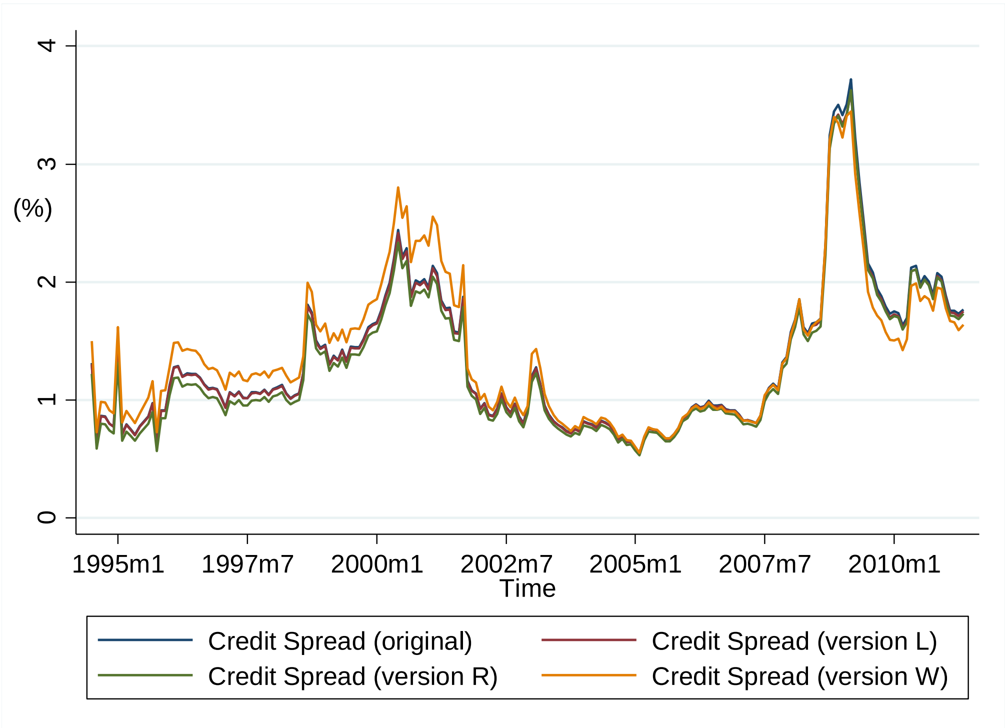

Figure 3. The Actual and Predicted EGZ Credit Spread

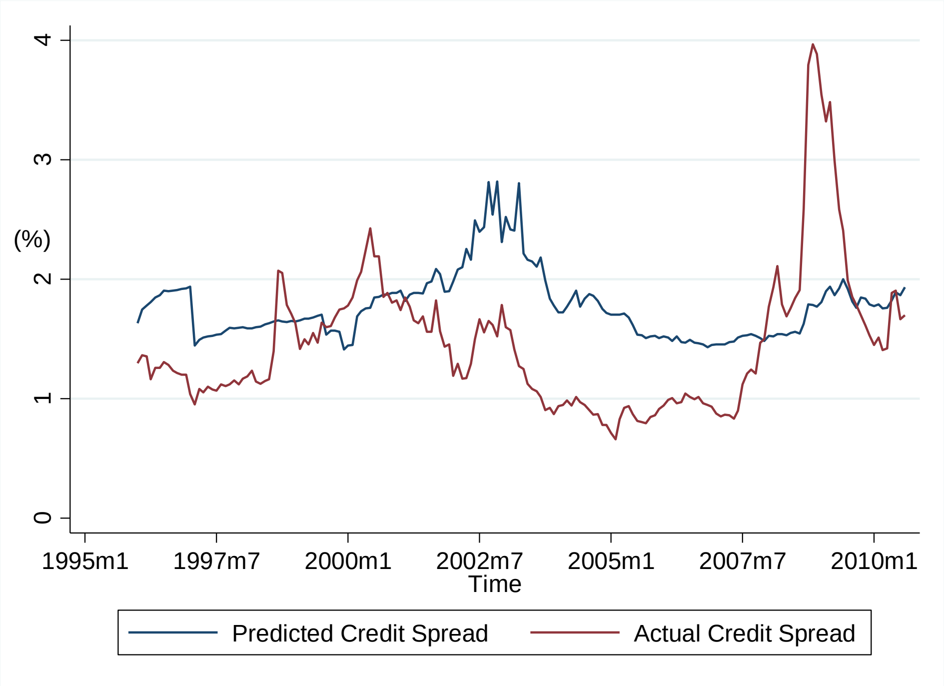

Figure 4. The EGZ Excess Bond Premium

Table 2.

Financial Indicator	Industrial Production			Unemployment Rate			Employment			Real GDP		
	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)
Credit 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

Forecast Horizon: 12 months / 4 quarters

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	
	Real GDP Growth					
	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)
Credit 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

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.

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)
Credit 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. 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 5. Credit 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
Credit Rating	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 6.

	Real GDP Growth					
Financial Indicator	**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 parentheses as per the CD p-value. *** p<0.01, ** p<0.05, * p<0.1

Table 7.

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. 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.

Financial Indicator	Real GDP Growth					
	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 9.

Financial Indicator	1 quarter		4 quarters		8 quarters	
	FE1	FE2	FE3	FE4	FE5	FE6
Real GDP Growth						
Term Spread	-0.575	-0.750*	-0.127	-0.753*	0.599	-0.0726
	(0.401)	(0.419)	(0.424)	(0.440)	(0.463)	(0.239)
Real Interest Rate	0.0160	0.0496	-0.112	0.0575	0.153	0.513**
	(0.197)	(0.184)	(0.312)	(0.276)	(0.248)	(0.254)
Predicted Spread	-0.668	-0.712*	0.0646	-0.328	-0.153	-0.578**
	(0.407)	(0.418)	(0.293)	(0.398)	(0.427)	(0.270)
EBP*AT	-2.337***	-2.209**	-1.872***	-2.098***	-1.192	-1.078*
	(0.764)	(0.835)	(0.589)	(0.660)	(0.956)	(0.607)
EBP*BE	-2.055*	-2.631**	-1.645*	-3.142**	-1.124	-3.051***
	(1.160)	(1.251)	(0.927)	(1.263)	(0.964)	(0.755)
EBP*FR	-1.517***	-1.349**	-0.662*	-0.441	-0.124	0.275
	(0.547)	(0.643)	(0.373)	(0.449)	(0.536)	(0.535)
EBP*DE	-1.702***	-1.845***	-1.306***	-2.003***	-1.042**	-1.987***
	(0.222)	(0.276)	(0.470)	(0.520)	(0.438)	(0.311)
EBP*UK	-2.276***	-2.414***	-1.522***	-2.457***	-1.087***	-2.466***
	(0.483)	(0.529)	(0.552)	(0.692)	(0.364)	(0.354)
EBP*IT	-2.229***	-2.663***	-1.580***	-2.556***	-0.869*	-2.056***
	(0.426)	(0.493)	(0.497)	(0.660)	(0.489)	(0.370)
EBP*NL	-1.839***	-1.802***	-1.732***	-1.977***	-1.322***	-1.700***
	(0.466)	(0.444)	(0.478)	(0.418)	(0.476)	(0.152)
EBP*SP	3.737***	5.575***	1.812**	5.093**		
	(0.882)	(1.621)	(0.709)	(1.950)		
Consumer Confidence		0.0833**		0.0824**		0.0414**
		(0.0354)		(0.0372)		(0.0182)
Economic Sentiment		-0.0972**		-0.209**		-0.258***
		(0.0458)		(0.0827)		(0.0648)
D4.CLI	0.275***	0.311***	0.142**	0.279***	0.0587	0.338***
	(0.0661)	(0.0811)	(0.0542)	(0.0932)	(0.0860)	(0.126)
Observations	204	204	204	204	172	172
R-squared	0.721	0.736	0.451	0.554	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	0.000	0.000	0.000	0.000	0.000	0.000
F-test (excl. UK)	0.000	0.000	0.000	0.000	0.000	0.000
F-test (FR, DE, NL)	0.889	0.733	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