EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

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Bond risk premia, macroeconomic factors and financial crisis in the euro area

No 1938 / July 2016

Abstract

This paper investigates the power of macroeconomic factors to explain euro area bond risk premia using (i) a large dataset that captures the nowadays data-rich environment (ii) the Elastic Net variable selection. We find that macroeconomic factors, in particular economic activity and sentiment indicators, explain 40% of the variability of risk premia before the crisis, and up to 55% during the financial crisis, and both for core countries (from 40% to 60%) and periphery countries (from 35% to 44%). Moreover, macroeconomic factor models clearly outperform financial indicators like the CP-factor and credit default swap (CDS) premia, even in periods of significant market turbulence.

JEL codes: E43, E44, G01, G12, C52, C55

Keywords: Bond risk premium, Macro Factors, Financial Crisis, Model Selection, Variable Selection

Non-technical summary

Understanding the determinants of bond risk premia is increasingly important for both investors and policymakers. Among those potential determinants, macroeconomic risks are particularly relevant, and economic indeed theory suggests that investors should be compensated for exposures associated with economic fluctuations. In addition, sovereign bond market developments have become increasingly important for monetary policy during the financial crisis, and linking them to the overall macroeconomic situation became crucial from a policy point of view as well.

This paper investigates the macroeconomic determinants of bond risk premia in the euro area (EA) bond markets. The EA bond markets are of special interest for several reasons. To start with, being denominated in a single currency, offer a unique opportunity for a multi-country analysis without exchange rate risk. EA bond markets are also ideal for analysing the determinants of bond risk premia during the financial crisis, for, together with the overall crisis, there was an intense sovereign debt crisis in some countries, which triggered an important public debate on the potential mispricing of risks in bond markets. By investigating the pricing of macroeconomic and financial risks in EA bond markets at country level prior and during the crisis this paper sheds new light on that debate.

We search for quantitative evidence on the extent to which macroeconomic factors are priced in in bond premia. To determine whether, when and by how much bond premia is related to price, economic activity, business sentiment or financial factors, or a combination of those, we employ the Elastic Net estimator (EN henceforth, Zou and Hastie, 2005),[1] a variable selection approach that helps overcome some specific challenges of euro area bond market data. First, we can evaluate a large number of potential determinants: 132 monthly macroeconomic indicators from nine macroeconomic groups, and, whenever possible, we also consider country-specific in addition to EA wide data (see the online appendix for details of our data and some additional results). Second, we can select observable factors based on their explanatory power for bond premia, which provides higher transparency and interpretability than principal components or other statistical techniques that instead summarise the information content of the explanatory variables (e.g. Stock and Watson 2002). Finally, the EN is particularly suitable for small sample analysis, which fits well with the short history of the EA and our goal of investigating the financial crisis impact.

We first document the strong impact of the financial crisis on bond risk premia across 11 EA markets. We show that the fairly strong commonality in bond risk premia dynamics across euro area

[1] The EN estimator belongs to a broad class of Least Angle Regression estimators (LARS) that are designed to rank the importance of every explanatory variable using a response vector (in our case excess returns) and help select a parsimonious model using a regularization parameter.

bond markets disappeared following the intensification of the financial crisis, and there was a significant de-coupling between two main groups, core (Austria, Belgium, Germany, Finland, France and the Netherlands) and periphery bond markets (Spain, Greece, Ireland, Italy and Portugal).

Despite the significant fluctuations in bond premia, macroeconomic factors display a strong predictive power throughout our sample. We construct predictive models by selecting the optimal combination of macro factors for each EA bond market. On average, such macro factor models can explain 38% of the variability of risk premia in EA bond markets before the crisis, and around 55% during the financial crisis. Moreover their performance is fairly consistent both for core (41% to 62%) and bond markets (from around 35% to 44%). Moreover, such macro models outperform standard and widely used models based on financial indicators, like the CP-factor (Cochrane and Piazessi, 2005) and/or CDS premia, and can handle well the rising segmentation in EA bond markets and the significant de-coupling between core and SMP countries during the financial crisis.

By shedding new light on the role of macro factors in bond markets and the feasibility of implementing an efficient variable selection in a data rich environment even in times of significant market turbulence, our results should be of interest for researchers, policymakers and market practitioners alike. First, our results provide support for the recent literature that aims at modelling the term structure of interest rates and the macroeconomy jointly to better understand the financial and debt crisis in the EA bond markets. Despite the crucial role of macroeconomic factors, the degree of heterogeneity in EA bond markets we found in this paper however warns against a limited number of macroeconomic variables as state variables in those term-structure models.

Policy analysis could also benefit from a robust interpretation of risk premia dynamics in the EA. Since it is crucial to understand which part of evolution of bond yields is related to the countries' economic fundamentals, taking into account news but also trends in the euro area macroeconomy is likely to be fundamental for the evaluation of the Asset Purchase Programmes introduced in early 2015 by the ECB. European policymakers as well as market practitioners could exploit the flexible modelling techniques introduced in this paper to measure such risks.

1 Introduction

Understanding bond risk premia has become increasingly important for both investors and policymakers since the financial crisis. Among the potential determinants of bond risk premia, macroeconomic risks are particularly relevant. Economic theory suggests that investors should be compensated for exposures associated with economic fluctuations. Moreover, as bond market rates are building blocks for pricing all financial assets, the pricing of macroeconomic risks in sovereign bonds is relevant fundamental for financial markets in general. In addition, sovereign bond market developments have become fundamental for monetary policy during the financial crisis, and linking them to the overall macroeconomic situation has become crucial from a policy point of view.

This paper investigates the macroeconomic determinants of bond risk premia in the euro area (EA) bond markets. EA bond markets are of special interest for several reasons. To start with, being denominated in a single currency, they offer a unique opportunity for a multi-country analysis without the need to account for exchange rate risk. EA bond markets are also ideal for analysing the determinants of bond risk premia during the financial crisis, for, together with the overall crisis, the intense sovereign debt crisis in some countries triggered an important public debate on the potential mispricing of risks in bond markets. By investigating the pricing of macroeconomic and financial risks in EA bond markets at country level prior and during the crisis this paper sheds new light on that debate.

Our analysis focuses on the predictive power of macroeconomic factors for bond premia, and on the impact of the financial and economic crisis on that predictive power. To determine whether, when and by how much bond premia is related to price, economic activity, business sentiment or financial factors, or a combination of those, we employ the Elastic Net estimator (EN henceforth, Zou and Hastie, 2005).[1] a variable selection

[1]The EN estimator belongs to a broad class of Least Angle Regression estimators (LARS) that are designed to rank the importance of every explanatory variable using a response vector (in our case excess

approach that helps overcome some specific challenges of euro area bond market data. First, we can evaluate a large number of potential determinants: 132 monthly macroeconomic indicators[2] including both euro area-wide and country-specific information that reflect the data-rich environment for euro area markets (Bernanke and Boivin, 2003, Bartsch et al, 2014). Second, we can select observable factors based on their explanatory power for bond premia, which provides higher transparency and interpretability than principal components or other statistical techniques that instead summarise the information content of the explanatory variables (e.g. Stock and Watson 2002). Finally, the EN is particularly suitable for small sample analysis, which fits well with the short history of the EA and our goal of investigating the financial crisis impact.

We first document the strong impact of the financial crisis on bond risk premia across 11 EA markets. Looking at monthly bond excess returns at the two-year maturity, we show that the fairly strong commonality in bond risk premia dynamics across euro area bond markets disappeared following the Lehman Brothers collapse. The crisis indeed led to wider heterogeneity and a significant de-coupling between two main groups, core (Austria, Belgium, Germany, Finland, France and the Netherlands) and periphery (Spain, Greece, Ireland, Italy and Portugal) bond markets, with bonds of the latter group eventually subject to the European Central Bank's (ECB) Securities Market Programme (SMP) purchases.

Despite the significant fluctuations in bond premia, we show that macroeconomic factors display a strong predictive power throughout our sample. First, we report that individual economic activity and economic sentiment indicators (around 15%) and prices (around 10%) explained a significant proportion of the variation in bond risk premia prior to the start of the crisis. Moreover, during the financial crisis their relevance, as that of other macroeconomic indicators (e.g. labour market) rose significantly.

returns) and help select a parsimonious model using a regularization parameter.

[2]We classify each indicator in one of nine well-defined macroeconomic groups, and, whenever possible, we also consider country-specific in addition to EA wide data (see Section 2 for details).

Using the EN methodology to select the optimal combination of macro factors, we construct predictive models for each EA bond market. We find that fairly parsimonious macro models that efficiently comprise the information content of different types of macroeconomic indicators exhibit a strong predictive power for bond premia across EA markets. On average, macro factor models can explain 38% of the variability of risk premia in EA bond markets before the crisis, and around 55% during the financial crisis. Moreover, their performance is fairly consistent both for core bond markets (41% to 62%) and periphery countries (from around 35% to 44%).

Our paper contributes to the growing literature on the determination of euro area sovereign bond yields (see Kilponen et al., 2015, for a recent insightful discussion). Most literature focused on sovereign yield spreads—i.e the spread between the yields of government bonds of EA countries with respect to their German government counterparts— or credit default swaps (CDS) premia. Most of these contributions assess financial factors to proxy for sovereign (credit and liquidity) and market risk.[3] This paper however looks at the pricing of macroeconomic factors in bond risk premia measured by excess bond returns.[4] Our work is closely related to the ample evidence on the link between macroeconomic factors and bond risk premia in the US bond market, exemplified recently by Ludvigson and Ng (2009), but also Cooper and Priestley (2009), Fontaine and Garcia (2011) and Huang and Shi (2012) among others. We extend that line of research to the euro area data, and investigate the role of almost all indicators regularly released by EA statistical offices by means of the EN variable selection approach, a recently-introduced empirical approach that is particularly suitable for euro area bond markets. This paper

[3]Among those many studies Beber et al (2009), Manganelli and Wolswijk (2009) and Favero et al (2010) study liquidity and credit risk, Fontana and Scheicher (2010) link bond spreads to credit default spreads, Zoli and Sgherri (2009) argue that fiscal conditions caused an increase in bond spreads and Borgy et al (2011) investigate the role of fiscal factors within an arbitrage-free affine term structure model.

[4]Pozzi and Wolswijk (2012) study EA excess returns. However, those excess returns are at weekly frequency, inflation-adjusted and include the pre-monetary union period (i.e. prone to exchange rate risk). The focus of their study is also identifying a common (latent) risk factor before the 2008 financial crisis.

therefore contributes to close the gap between available evidence for US and euro area bond markets.

Our findings suggest that macroeconomic factors contribute substantially to the understanding of the dynamics of risk premia in euro area bond markets. We also find that indicators of financial market conditions, both prior to and during the financial crisis, help explain bond premia. But financial factors appear to be quantitatively less important than macro factors in euro area bond markets. For example, our macro factor models outperform financial indicators like the CP-factor (Cochrane and Piazessi, 2005), and other financial indicators, like credit default swap (CDS) premia and government debt dynamics whose analysis during the financial crisis and, in particular, for the euro area, has been the focus of attention in most of the related sovereign risk premia literature.

The paper is organised as follows. Section 2 introduces the euro area bond markets data, namely bond yields and risk premia, and macroeconomic and financial factors. Section 3 explains in detail our methodological approach, in particular the factor evaluation and model selection criteria. Empirical results for individual factors and the selected models are presented in Section 4. Section 5 provides evidence that our findings are robust to different model selection criteria and the possibility of summarising the information content of individual factors by macroeconomic groups. Finally Section 6 concludes.

2 Euro area bond risk premia and macroeconomic factors

We measure bond risk premia using the one-year excess bond returns–buy a longer-term bond by borrowing at the one-year rate and sell it in one year–observed in the market. Specifically, let $r_{t+12}^{(n)}$ be the continuously compounded (log) return on an n-year discount bond in period $t+12$ and $y_t^{(n)}$ is the (log) yield on the nth-year bond, then *excess returns* are defined as $rx_{t+12}^{(n)} = ny_{t+12}^{(n)} - (n-1)y_{t+12}^{(n-1)} - y_t^{(1)}$. To calculate those excess returns in EA bond markets we estimate daily zero-coupon term structures for each country using the Nelson-Siegel-Svensson parametric method,[5] which is the approach used for the calculation of the official EA-wide yield curve(s) published daily by the ECB, but also by the Board of Governors of the Federal Reserve and many other central banks (see BIS, 2005). Throughout this paper we only discuss results for premia on two-year maturity bonds. Our choice is motivated to have liquidity conditions across euro area bond markets, particularly since the intensification of the financial turbulences in 2008, that are sufficiently homogeneous to compare the pricing of the macroeconomic conditions on bond yields and risk premia. In any case, the term structure of bond risk premia in euro area bond markets was upward sloping over our sample, and our key findings hold for longer maturities as well.

Our bond data source is MTS, a high-quality dataset based on the largest electronic trading platform in Europe that is used in the regular estimation of the ECB's euro area zero-coupon yield curve. The MTS dataset starts in late 2004, so our sample starts in 2004:09. From 2010:05 the ECB purchased Greek, Irish and Portuguese government bonds, and subsequently, Italian and Spanish ones, as part of the Securities Market Programme (SMP). To isolate our analysis from the distortions introduced by those purchases, our empirical analysis ends in 2010:04. As recently shown by Kilponen et. al (2015), the dynamics of bond yields in euro area bond markets beyond mid-2010 has also been strongly influenced by ECB's policy announcements and direct interventions whose analysis requires the use of higher-frequency than that at which macroeconomic data are compiled and released. We use month t factors to forecast excess returns 12 months later (in $t + 12$). As the short sample is prone to (local) non-stationarity,[6] we difference the series but denote the stationarised excess returns as simply $rx^{(n)}_{t+12}$.

We will consider two different periods: a pre-crisis period between 2004:10 and 2008:08, and a (financial) crisis period between 2008:09 and 2010:04. The number of

[5] See Nelson and Siegel (1987) and Svensson (1994)

[6] Some series still exhibit a trend after differencing, and we remove this trend as well.

months in each time frame is therefore $T_{Pre-Crisis} = 33$ and $T_{Crisis} = 21$ respectively. A goal of this paper is to shed some light on the debate on the potential mispricing of risks in euro area bond markets both ahead and during the financial and debt crisis in the euro area. To focus the discussion we also define two bond market groups: first, a *core* group composed by Austria, Belgium, Germany, Finland, France and the Netherlands bond markets and another group comprising the bond markets of Greece, Ireland, Portugal, Spain and Italy. The latter bond markets were under severe stress in the latter part of our sample, which eventually triggered direct interventions by the ECB in the form of bond purchases in those specific markets under the *Securities Market Programme* (SMP) to restore proper functioning. For the sake of clarity, we will therefore refer to this latter group as SMP countries.

2.1 Risk premia in euro area bond markets

To our knowledge, we are the first to study excess returns in the EA and before investigating its determinants, we first document the evolution of risk premia in bond markets. The impact of the financial crisis is a crucial aspect to note. Before the start of the financial crisis, bond premia were positive, displayed a strong positive autocorrelation (Table 1) and tended to move relatively closely together across all EA bond markets. In terms of dynamics, premia in EA bond markets started to increase gradually ahead of the intensification of financial turbulences in September 2008 both for core (left panel) and SMP (right panel) bond markets (Figure 1).

The start of the financial crisis however triggered some important differences in bond premia over EA bond markets. First, in terms of levels there was a significant decline at the beginning of the financial crisis, in the aftermath of the Lehman collapse, which was probably related to strong flight-to-safety flows into sovereign bonds for all EA bond markets at the time (see Baele et al. 2013). Thereafter, as the financial and economic crisis deepened, there was an increasing differentiation of sovereign issuers within the EA reflected in the higher heterogeneity in excess return dynamics across bond markets. Specifically, bond premia in core bond markets remained relatively compressed and continued to exhibit a strong comovement among them, partly as a result of further flight-to-safety and flight-to-liquidity flows from SMP bond markets (see Garcia and Gimeno, 2014). In contrast, in SMP bond markets premia developments started to display wider divergences both within the SMP and with respect to the core group.

Figure 1 suggests that bond premia and bond yields were strongly correlated among all EA bond markets prior to the financial crisis, and the comovement was already somewhat stronger among the core than among the SMP markets. To provide some quantitative evidence on the evolution of the bond premia comovement in EA bond markets, Table 2 reports average correlation coefficients of level and stationarised excess returns and yields.[7] Table 2 corroborates that the financial crisis increased market segmentation across EA bond markets, and that the segmentation was however rather asymmetric across bond markets. Average excess return correlations declined in the crisis period for the EA as a whole (that is when we consider all the EA bond markets in the average). But there was a substantial difference when bond market groups are considered: while within the SMP group there was an overall decline in comovement in line with the effect for the EA as a whole, core bond markets maintained a fairly high degree of comovement over the financial crisis period. This suggests that the financial crisis led to rather heterogeneous dynamics in the risk premia in EA bond markets but such a divergence was particularly stronger in the case of SMP bond markets, even among them, while premia on core bond markets tended to move much closer together.[8]

[7] We calculate (average) correlation coefficients as follows $correl_I = \left(\sum_i^I \sum_j^{I-1} correl(rx_i^{(n)}, rx_j^{(n)})\right) / \left(\frac{I^2-I}{2}\right)$ for $i \neq j$, three different country groups $I = \{\text{All}, \text{Core}, \text{SMP}\}$ and where the vector of excess returns rx has length either $T_{Pre-Crisis}$ or T_{Crisis}.

[8] Average correlation coefficients for bond yield levels display a similar pattern.

2.2 Factors

We start by describing the macroeconomic (and financial) factors we use to better understand the divergences in bond premia dynamics reported above.

Macroeconomic factors. We consider 132 macro factors available within the EA. We classify them into nine macroeconomic groups: 1. Activity (*economic activity indicators*: industrial production, orders, sales, permits...); 2. Sentiment (*economic sentiment indicators*: business, consumer, sectoral confidence); 3. Labour (*labour market indicators*: various unemployment rates, employment indices); 4. Trade (Extra and Intra EA trade); 5. FX (exchange rates); 6. Mon./Int. (*Monetary and interest rate indicators*: Euribor rate, monetary aggregates); 7. Stocks (*stock market indicators*); 8. Prices (*price indicators*: Commodities, consumer and producer price indices); 9. US (various factors of the US economy). For 5 of those 9 groups (Activity (1), Sentiment (2), Labour (3), Trade (4), Stocks (7), Prices (8)), we also consider *country-specific factors,* that is individual macro factors (e.g. price developments or business confidence) that are specific to the country of the respective bond market. The full list of macroeconomic factors is displayed in Garcia and Werner (2015), which also details their transformation to achieve stationarity in line with the literature on the construction of diffusion indices (see Stock and Watson, 2002). Furthermore, every factor has been standardized. Formally, those macroeconomic factors comprise matrix $\vec{Z}$, where $t = 1, ..., T$ and $k = 1, .., K$.

Specific bond market and crisis factors. In an influential contribution, Cochrane and Piazessi (2005) showed that a single factor based on a linear combination of forward rates is capable of explaining more than 30% of the variation in next years' bond premia in bonds for maturities up to five years, which suggests that a substantial part of the information that is necessary to predict future bond premia is contained in the term structure.[9] Here, we compute the CP-factor for the EA bond markets as benchmark against which to assess the explanatory power of macroeconomic factors.[10]

The fiscal deterioration in many euro area countries during the financial crisis could also be a potential factor behind excess returns in their respective bond markets. Unfortunately, fiscal variables (public deficit, public, deficit "debt-to-gdp" ratio, etc) are not available at monthly frequency. To control for fiscal deterioration in our analysis, we construct a monthly indicator of the *financing needs,* of each country by adding the public deficit forecasts published by European Commission and the maturing debt for each country over the next 12 months. Sovereign default risk has been a recurrent topic for some EA countries and indeed the price of *credit default swaps* has drawn significant attention since early 2009. To explicitly control for default risk in bond premia we investigate the explanatory power of sovereign CDS premia during the crisis period. Prior to 2007:07 the market of CDS had been absent for most EA bond markets.[11]

3 Empirical Approach

To explore the explanatory power of macro factors for EA bond risk premia, we use k factors[12] in month t to forecast excess returns 12 months later $(t + 12)$ in each bond market using a standard predictive regression

$$rx^{(n)}_{t+12} = \beta_0 + Z_t\beta + \epsilon_{t+12} \tag{1}$$

where Z_t is the $1 \times k$ factor matrix with dimensions, with k being the dimension of the vector of selected factors, and β_0 a constant.

[9] Several types of predictors have been proposed in the US bond premia literature. Specifically, we cannot relate our study to the cyclicality of premia (Cieslak and Povala (2013)). The short time dimension of our sample cannot be used to test all of these predictors and does not allow us to run a lot of the tests Cochrane and Piazzesi (2005) conduct.

[10] Due to potential non-stationarity concerns in the forward rates as well as the one year yield, we can only replicate a transformed version of the CP-factor. We differentiate -and if necessary detrend- the forward rates to derive the stationary CP-factor. In order to stay consistent with our subsequent regressions we also standardized this factor. We explain the details in Garcia and Werner (2015).

[11] We also first-difference the variables, and, when necessary, remove a linear trend from these variables.

[12] Factors refers generically to macro factors, the CP-factor and the potential crisis factors.

Our empirical strategy proceeds in two steps. First to select the most promising variables, we rank the factors by their explanatory power. In a second step, we construct an optimal linear model by determining the factors to be included.

3.1 Variable selection

To identify the best predictive factors, we apply the Elastic Net (*EN*) methodology to the bond risk premia analysis.[13] The EN estimator, a variable selection approach proposed by Zou and Hastie (2005), belongs to the family of penalized (nonlinear) regression estimators, which extend the minimisation of the residual sum of squares of the regression by adding a penalty (or regularisation) based on the optimal number of parameters[14]. Formally, the estimates from the *(naive)* EN criterion are defined by

$$\boldsymbol{\beta}(EN) = \arg\min_{\beta} \left(\left\| cen\left(r\vec{x}^{(n)}\right) - \vec{Z}\boldsymbol{\beta} \right\|^2 + \lambda_1 \left|\boldsymbol{\beta}\right|_1 + \lambda_2 \left\|\boldsymbol{\beta}\right\|^2 \right) \tag{2}$$

where $|\beta|_1 = \sum_{p=1}^{P} |\beta_j|$, the penalty parameters λ_1 and λ_2 have positive weights.[15] The advantages of the EN selection criterion for our goal in this paper can be better understood by considering two other criteria it nests as special cases, namely the standard ridge regression (if λ_1=0 and $\lambda_2 = 1$) and Tibshirani's (1996) *Least Absolute Shrinkage and Selection Operator* (LASSO if λ_1=1 and $\lambda_2 = 0$).[16]

The penalty coefficient λ_1 contributes to both shrinkage and variable selection. The penalty coefficient λ_2 helps to overcome two problems of the LASSO selection criterion, which are particularly relevant in our case. First, when many potential factors are highly

[13]Although Huang and Shi (2012) and Bonaldi et al (2014) apply the adaptive lasso (a very similar procedure) and the elastic net, respectively, there are important differences with respect to their applications. The former uses the estimator to create a single macro factor to forecast US bond premia. The latter uses this estimator to tackle a large number of controls. This paper further exploits the advantages of the EN methodology by searching through a large number of series in small samples.

[14]We implement the EN using the MATLAB code by Sjöstrand (2005)

[15]$cen\left(r\vec{x}^{(n)}\right)$ is the mean centered vector of the dependent variable $r\vec{x}^{(n)} \equiv (rx^{(n)}_{1+12,i}, \cdots, rx^{(n)}_{t+12,i}, \cdots, rx^{(n)}_{T+12,i})$.

[16]The EN nests two shrinkage procedures (LASSO and ridge regression) and one would have to re-scale to the final coefficient vector $\widehat{\boldsymbol{\beta}}(EN)^* = (1+\lambda_2)\widehat{\boldsymbol{\beta}}(EN)$. However, in our application we only use the LARS-EN ranking to find the optimal linear model so the re-scaling is unimportant.

correlated (for example, if they belong to the same macroeconomic groups described in section [2.2]) the LASSO criterion tends to select only one factor from the group and the within-group selection is often not robust.[17] Second, when confronted with a data set in which the number of potential factors is much higher than the number of observations ($k >> T$) the LASSO criterion can select at most T factors by the construction of the optimization problem. This is an important limitation in our case as we aim at investigating the explanatory power of a large number of macroeconomic time series over the financial crisis period. The quadratic term in the EN *(naive)* elastic net penalty, by ensuring that the selection problem is strictly convex, favours within-group variable selection even in very short samples.[18] The EN criterion, therefore, offers some advantages with respect to ridge regression, LASSO and OLS itself in terms of prediction and model interpretation.

The EN is implemented using Least Angle Regression (LARS). Initially, all factor coefficients are set to zero ($\vec{r} = \vec{y}$ and $\hat{\beta}_k = 0$ for all k), and we search for the $\vec{z}_{selected\ k}$ vector of predictors most correlated with our vector of excess returns $\vec{r}$. At each iteration, the algorithm computes the residuals of a regression of the response vector on the by-then selected factors, and expand the set of selected factors by moving $\hat{\beta}_k$ in the direction of the sign of $correl(\vec{r}, \vec{z}_{selected\ k})$ until some other factor $\vec{z}_{new}$ is as strongly correlated with the current residual as the already-selected factors $\vec{z}_{selected\ k}$ are.[19]

[17] Formally, the LASSO optimisation problem is convex, but not strictly convex. Moreover, it is not well-defined unless the bound on the L_1-norm of the coefficients is smaller than a certain value.

[18] See Zou and Hastie (2005) and Bai and Ng (2008) for additional details.

[19] Specifically, we start with an initial estimate of the response vector of excess returns $\widehat{\boldsymbol{\mu}}_0 = \vec{Z}\boldsymbol{\beta}_0 = \vec{0}$, and select the covariate $\vec{z}_1$ with the highest absolute correlation with the residual vector $\vec{r}_0 \equiv cen(r\vec{x}^{(n)}) - \widehat{\boldsymbol{\mu}}_0$. In the case of two covariates $K = 2$ and $\vec{Z} = [\vec{z}_1, \vec{z}_2]$ we update $\widehat{\boldsymbol{\mu}}_0$ in the direction of $\vec{z}_1$ to $\widehat{\boldsymbol{\mu}}_1 = \widehat{\boldsymbol{\mu}}_0 + \widehat{\gamma}_1\vec{z}_1$. $\widehat{\gamma}_1$ is the value that makes the difference between the projection of $cen(r\vec{x}^{(n)})$ onto the linear space of $\vec{Z}$ and the estimated response $\widehat{\boldsymbol{\mu}}_0$ -that is $proj(cen(r\vec{x}^{(n)}))|\mathcal{L}(\vec{Z}) - \widehat{\boldsymbol{\mu}}_0$ - is equally correlated with $\vec{z}_1$ and $\vec{z}_2$, so that $proj(cen(r\vec{x}^{(n)})|\mathcal{L}(\vec{Z}) - \widehat{\boldsymbol{\mu}}_1$ bisects the angle between $\vec{z}_1$ and $\vec{z}_2$ and $correl(\widehat{\boldsymbol{\mu}}_1) = correl(\widehat{\boldsymbol{\mu}}_1)$. If $\vec{u}_2$ is the unit vector along the bisector, then the next LARS estimate is $\widehat{\boldsymbol{\mu}}_2 = \widehat{\boldsymbol{\mu}}_1 + \widehat{\gamma}_2\vec{u}_2$. In the case of $K > 2$ the algorithm becomes more complex, and we refer to Efron et al (2004) for a detailed description of the exact steps.

Two steps in the selection procedure are worth stressing. First, at each iteration p we find the factor k_p with the highest correlation with the current residual

$$k_p = \underset{k}{max}\{|correl_p = \vec{Z}'(cen(r\vec{x}) - \widehat{\boldsymbol{\mu}}_{\mathcal{A}_p})|\}, \tag{3}$$

then update $\widehat{\boldsymbol{\mu}}_{p+1} = \widehat{\boldsymbol{\mu}}_p + \widehat{\gamma}_{p+1}\vec{u}_{p+1}$, and move that factor into the *selected set*. We proceed along equiangular vectors $\vec{u}_{p+1}$ and the coefficient $\widehat{\gamma}_{p+1}$ gets smaller as factors are added to the selected set.

The first penalty coefficient adds a sign restriction to the model. The vector of estimates using the factors of the active set at p is $\boldsymbol{\beta}_p$. The sign of each β_{kp} has to agree with the sign of $correl_{kp}$ for each k, that is $sign(\widehat{\beta}_k) = sign(correl_{kp})$. Any k failing this condition is set back to the inactive set, and the factor selection continues until all factors are evaluated. Due to this restriction the maximum number of iterations is equal or larger to the number of factors ($p_{max} \geq K$).

To implement the second penalty, equation (2) can be reformulated as a lasso-type problem $L(\gamma, \vec{\beta}) = \|cen(r\vec{x^{(n)}})^* - \vec{Z}^*\boldsymbol{\beta}^*\|^2 + \gamma|\boldsymbol{\beta}^*|_1$, where $\gamma = \lambda_1(1+\lambda_2)^{-1/2}$, $\boldsymbol{\beta}^* = (1+\lambda_2)^{-1}\boldsymbol{\beta}$ and

$$\vec{Z}^*_{(obs+K)\times K} = (1+\lambda_2)^{-1/2}\begin{pmatrix} \vec{Z} \\ \lambda^{1/2}\vec{I} \end{pmatrix} \quad cen\left(r\vec{x^{(n)}}\right)^* = \begin{pmatrix} cen\left(r\vec{x^{(n)}}\right) \\ 0 \end{pmatrix} \tag{4}$$

3.2 Model Selection

Once the individual series are ranked according to their marginal explanatory power, the optimal model —i.e. the optimal set of factors— can be determined through a model selection criterion. To determine the set of factors that define the optimal model, the adjusted R^2 of the linear predictive regression

$$\bar{R}^2 \equiv 1 - \frac{RSS}{TSS}\frac{obs-1}{obs-k^\star-1} \tag{5}$$

where RSS is the residual sum of squares, TSS is the total sum of squares, and $k^\star$ is the optimal number of macro factors. Existing literature favours information criteria like the AIC and the BIC (see Bai and Ng, 2008),[20] which focuses on minimizing RSS, and may however fail to address the close within-group collinearity among factors. The sample variance of factor j can be expressed as

$$var\left(\beta_j\right) = \frac{s^2}{(n-1)\widehat{var}(z_j)} \frac{1}{1-R_j^2} \tag{6}$$

where R_j^2 is the unadjusted R^2 for the regression of z_j on all the other k factors except j itself. R_j^2 increases as collinearity increases, but also the variance of β_j would be inflated.[21] To avoid selecting an overfitted model by taking into account the increase in the variance of individual factors, we follow Stine (2004) and apply a t-test criterion to determine the set of factors $k^\star$ in the optimal model.[22] Specifically, we start with the top ranked factor, and continue adding factors to the model until step $k^\star + 1$ in which $|t_k|$ for any $k = \{1 \ldots k^\star + 1\}$ is smaller than the critical value for at least one factor.

As both R_j^2 and $var\left(\beta_j\right)$ of equation [6] increases, RSS_j decreases, and standard information-criteria tend to select the model with the lowest RSS. As argued by Stine (2004) and others,[23] a t-test criterion— or hard thresholding —would instead penalize an increasing variance of β_j and thereby favours the selection of a more parsimonious model. Note that, although a t-test criterion may be potentially problematic when conducting simultaneous inference, in our application we proceed sequentially from the most important factor (in terms of predictive power) and search for additional factors along the EN ranking, a ranking that already takes into account the dependence structure across all K factors.

There are two additional advantages of applying a t-test criterion for our analysis here. First, we can determine standard errors $STDev(\hat{\boldsymbol{\beta}})$ that are robust to serial cor-

[20] Bai and Ng (2008) discusses three ways to use EN-ordered variables: i) They estimate the principal component from the first 30 series that EN selects. This method conflicts again with our short samples as well as the limited interpretability of the derived statistical factor. ii) The first five factors enter the regression equation which is rather arbitrary. iii) They use an information criterion.

[21] $1/\left(1-R_j^2\right)$ of 6 is also called the variance inflation factor.

[22] Stine (2004) suggests to apply the squared t-statistics t^2, where $t \equiv \hat{\beta} \diagup STDev(\hat{\beta})$. It is calculated at every step k using forward stepwise regression. By adding the ranked factors to the model until t falls below *the risk inflation factor* the threshold $2 * \log k$.

[23] See also Efron et al (2004).

relation.[24] Secondly, as the t-test critical distribution depends on the sample size T, that is especially important for the individual bond market regressions where $T \ll 50$. As part of robustness checks, we, however, report the results of several model selection criteria (AIC, AIC$_c$, BIC, etc) in Section 5.2 below, which corroborate the arguments in this section (see Table 6).[25]

The EN approach offers some key advantages for our purpose in this paper. First, following the increasing use of diffusion indexes in recent years (see e.g. Stock and Watson, 2002 among many others), Ludvigson and Ng (2009) calculated principal components from a rich set of macro factors and explore their predictive power for excess returns in the US bond market. Using a similar set of variables but our approach identifies directly-observable factors, which provides a transparency that is important for policy makers and market participants.

Second, the approach proposed in this paper selects macro variables on the basis of their explanatory power for excess returns and not by their capability to summarise a set of macroeconomic indicators, and can be efficiently used even in small samples including the 2008:09-2010:04 period of intense turbulence in the EA sovereign bond markets.[26] In order to maintain interpretability (for example Beber et al. , 2013), we select just the first principal component from a specific macro group. However, even selecting a factor from each of the 9 groups as well as the 6 country-specific macro groups listed in Section 2.2, 15 different factors would most likely overfit the regression equations in the samples of interest, particularly in the financial crisis period. Secondly, there is a potential loss of explanatory power. A particular macro group could be described by

[24]This is important for excess returns because the continuously compounded annual return has an MA(12) error structure under the null hypothesis that one-period returns are unpredictable. In the case of individual bond market regressions we achieve robust standard errors using the popular Newey-West covariance matrix estimator and determine the lag length using the Bartlett kernel.

[25]In case, LARS-EN ranking in combination with the t-test criterion selects a single factor which has lower explanatory power than the factor with the highest explanatory power, we will overwrite the EN selection and use the latter.

[26]In addition, with a limited number of time series observations ($T \leq 33$) formal tests to determine the optimal number of principal components to extract for each macro group would have very weak power (see Bai and Ng, 2002) and Onatski (2009).

more than just one principal component. Indeed, as we show in Section 4.1, some macro groups have factors with heterogeneous dynamics, and these heterogeneous factors have also considerable explanatory power with respect to bond premia.

Our approach can also be interpreted in terms of a latent factor structure $z_{kt} = \lambda_k' f_t + e_{kt}$, where f_t is an $r \times 1$ vector of latent common factors, λ_k the corresponding $r \times 1$ vector of loadings, and e_{kt} a vector of errors. We assume that our macro factors z_{kt} are still determined by f_t, which we know is not observable and for the reasons given above, the optimal number of statistical factors r cannot be determined. However, by assigning macro factors to different macro groups, we understand where the overall dynamics originates from. The macro factor itself indicates for example, the industry sector (primary or secondary) or whether it is a durable or non-durable. Therefore, in our regression tables, we will report both: the macro group as well as the name of the macro factor itself. For example, although some selected factors, such as the number of new passenger cars, might be too specific to describe economic activity, it is indeed a variable widely watched by market participants.

4 Empirical findings

This section presents our main results on the predictive power of macro factors for bond premia. First, we assess the explanatory power of individual macro factors. Then, we report the composition and performance of the models constructed from a combination of the best macro factors selected following the EN approach described in Section 3.

4.1 The explanatory power of individual macro factors

We first provide an overview of the marginal predictive performance of macro factors based on the R^2_{ki} in predictive regression (1) for each macro factor k and bond market i. Given the large number of potential factors we consider, we discuss herein a truncated distribution of R^2_{kim} within macro group m.[27] Whisker plots in Figures 2 (a) - (d) show this truncated distribution distribution of R^2_{kim} for Pre-Crisis (core (a) and SMP (b)) and Crisis (core (c) and SMP (d)). For each of the 9 macro groups[28] and bond market, the R^2_{kim} of the *best performer* factor (k_{best}) is marked by "▲", and the line connects the average R^2_{kim} (marked by a "•") of the top 25 performers in each macro group.[29] The analysis of the marginal predictive power of macro factors provides two main insights. First, as regards the type of macroeconomic factors more relevant for bond risk premia, the factors with the highest average predictive power for bond premia belong to the economic activity (e.g. retail sales), economic sentiment (e.g. consumer inflation expectations) and prices (e.g. services inflation) groups. This qualitative finding is relatively robust along the full sample, but quantitative changes over the crisis period are also worth noting. Specifically, before the crisis, the average maximum predictive power achieved by any individual factor within the group is slightly higher in the Core than in SMP bond markets, but differences across bond markets are nonetheless limited. During the crisis, the predictive power of macro factors rose, and in particular for those in the economic activity and economic sentiment groups doubled on average to around 30%. Moreover, it did so in both Core and SMP bond market groups.

Second, despite those common trends, Figure 2 also shows that the dispersions across individual factor performance rose significantly during the crisis, and for all 9 macro groups, which suggest that it is important to account for heterogeneity in modeling the euro area bond markets and the impact of macro factors. For example, within the core group on average the best indicators of the Labour, Trade, Stocks and US macro groups rise to around 25%, while for the SMP group they remain around 10%.

[27] The appendix of Garcia and Werner (2015) depicts the R^2_{ki} for each factor and country in bar graphs.

[28] Macro groups which have a country-specific counterpart are combined with their respective EA group.

[29] Whisker ends and the connecting vertical lines depict the 9th and 91th percentile.

4.2 Model composition and performance

We now move beyond individual factors and search for the optimal (multifactor) model. Specifically, we exploit the EN properties to select an optimal combination of all macro factors by selecting those with the highest explanatory power while at the same time taking into account the different information they contain (see Section 3). In the light of the evolution in bond premia over our sample (see Figure 1) and the evidence on the marginal predictive power of the factors above, we search for the optimal combination of factors over two separate periods, the pre-crisis period 2004:10-2008:08, and the crisis period 2008:09-2010:04. From left to right, the columns in Tables 3 and 4 list the bond market, sample period, explanatory power of each model, name of macro series, sign of the estimated coefficient, the additional explanatory power of each model with respect to the CP-factor model, the macro group of the respective macro factor.[30]

4.2.1 Pre-Crisis period

Tables 3 and 4 summarise the performance and composition of the selected models for Core and SMP bond markets, respectively. In terms of predictive performance, before the crisis intensified, the selected models for each bond market explain on average around 38% of the variation in bond premia. The model performance tends to be somewhat higher for the Core (on average 41%) than for the SMP (at 35%) bond markets, but there are some important differences across bond markets in both country groups. In the core group, the $\bar{R}^2$ ranges from a 63% for Finland (using 7 factors) to a 23% in the German bond market (using only 2 factors). Within the SMP group, Greece has the highest $\bar{R}^2$, 53% using 6 factors, while the worst performing model is for Spain, where no macro factor is selected and the model relies exclusively on the CP-factor.

In terms of the composition, selected factors in most markets often belong to economic activity and economic sentiment indicators, in line with the individual factor

[30] Brackets indicate the series number and (Country) denotes a country-specific series.

results discussed in the previous section. Interestingly, market investors seem to play substantial attention to the information from consumer surveys. Two of the factors selected for most countries are consumers' inflation perceptions (over the previous 12 months) and their "savings expectations for the next 12 months". Inflation perceptions do have a positive effect on bond premia, most likely on account of the inflation risk premia. Increased savings expectations in contrast reduce premia. Since they may be interpreted as an indicator of future demand and therefore economic activity, this suggests that expectations of an increased real activity pushed premia down in our sample. In general across markets, observed economic activity factors have an overall negative impact on premia, suggesting that increased real economic activity already contributed to reduce premia ahead of the crisis, a finding that helps understand the significant compression of bond yields and premia over the pre-crisis period, and, as we will see, its subsequent rise in the light of the severity of the economic crisis.

4.2.2 Financial crisis period

The performance of the selected models improves significantly in most bond markets during the financial crisis period, and on average around 60% and 45% of the variation in bond risk premia in Core and SMP countries respectively can be explained. Importantly for our goal in this paper, the fact that the selected models incorporate a significant larger number of macroeconomic factors during the crisis seems crucial for their improved performance. This finding is also consistent with the strong role also found for macro factors at individual level (see Section 4.1) and suggest a stronger pricing of the macroeconomic indicators among bond market investors. Indeed, the composition of selected models shifts towards macro factors.

Specifically, in SMP markets, the $\bar{R}^2$ of the selected models increases from 22% to 67% for Spain when 4 macro factors are included, 46% to 50% for Italy $\bar{R}^2$, although the number of factors declines from 5 to 3, and from 29% to 43% for Portugal (3 to

1 factors). In contrast, for Ireland and Greece bond markets the model performance deteriorates, possibly reflecting severe pricing distortions in their bond markets early on in the crisis.[31] In core bond markets, despite the more limited rise in premia (see Figure 1), $\bar{R}^2$ ranges between 47% for the French (34% in the pre-crisis period) and 77% for the Austrian (50% in the pre-crisis period) bond market, and, overall, if the CP-factor remains selected, is also complemented by other macro factors.

In terms of factor composition, the selected models still favours real economy factors from the Economic Activity and Sentiment macro groups as before the crisis. But labour market indicators become increasingly important, most likely reflecting both the severity of the economic crisis and the implications of the increasing unemployment for public finances. Interestingly, there was also a shift away from inflation expectations towards expectations of business conditions in the retail sector as well as unemployment expectations, building permits and assessment of stocks, which became the most important economic activity factors. Increased activity in the manufacturing sector and employment have a negative impact on premia, which again stresses that accounting for the economic nature of the crisis is likely to be fundamental in understanding bond premia in the euro area.

Two other differences between the Core and the SMP bond markets are also worth noting. First, SMP markets solely rely on economic activity and sentiment indicators, but, for core bond markets, trade, labour and US macro indicators are also selected. Second, some of our crisis models also include country-specific macro factors, particularly for SMP the group. This finding, which suggests that investors pay more attention to country-specific macro factors once a crisis arrives, is consistent with the "wake-up call hypothesis" for risk pricing (e.g. Bekaert et al, 2014) .

[31]Two things should be noted. First, the number of observations drops from 46 months (pre-crisis) to 21 months (crisis) and this also implies a loss of statistical power. Second, these results also indicate that factors which are important explain largely the same kind of variation and adding more factors to the model will not increase the explanatory power or any other factor does not have any explanatory power. Section 5.3 explores this particular question further.

4.3 Macroeconomic factors versus the CP-factor

Our results suggest that macro factors do contribute substantially to the understanding of the dynamics of risk premia in euro area bond markets. Moreover, the intensification of the financial crisis since 2008, if anything, reinforced the role of macro factors in explaining the rise and the dynamics of bond risk premia in all euro area markets. Importantly, our search for the best combination of factors also takes into account financial factors, ranging from monetary policy rates to the CP-factor, a natural benchmark reference in terms of bond risk premia analysis. Indeed, we also find an important role for indicators of financial market conditions, both prior to and during the financial crisis, in explaining bond premia, which is logical given the nature of the crisis and the fact that the bond premium is also a financial market variable.

But financial factors appear to be quantitatively less important than macro factors in euro area bond markets. Prior to the intensification of the financial market turbulences in late 2008, at least one interest rate factor is selected in the preferred model for each bond market, either the Euribor-OIS spread (mainly for core bond markets), or the CP-factor (in SMP bond markets). Importantly, even though the CP-factor is selected as a factor across the EA before the crisis, macro factors still add substantial explanatory power to the combined models: the $\bar{R}^2$ of combined models is around 25% higher than only using the CP-factor, on average across countries, 13%, well below evidence for the US bond market (Cochrane and Piazzesi, 2005). The financial crisis led to higher heterogeneity in the performance of the CP-factor across EA bond markets, in that, while the average explanatory power of the CP-factor model rose in core bond markets (12% to 31%), it declined in SMP bond markets (15% to 6%). Consistent with that lower explanatory power, in all SMP countries for which the CP-factor was part of the selected model in the pre-crisis period, it is replaced by macro factors during the crisis period, and the selected models are nonetheless capable of explaining 44% of all variation across the crisis period.

We find that the superior performance of macro factor models over the CP-factor in explaining bond risk premia has two important implications. First, in a data-rich environment in which markets nowadays operate, a single factor, either constructed along the lines of the CP-factor or as a principal component, is unlikely to be capable of summarising all the necessary information for a correct pricing of risks. In addition, and despite the financial origin of the 2008 crisis, the market turbulence was quickly spreading to the real economy in the euro area and worldwide, and it is, therefore, logical that the premia requested in financial market also took into account direct macroeconomic information to identify the risks of a given financial investment.

5 Robustness checks

Previous sections reported a strong role of macroeconomic factors in explaining the dynamics of risk premia in euro area bond markets. This section provides assessment of the robustness of our findings in several dimensions. First, we compare the performance of the macro factor models we select in this paper with that of CDS premia and debt dynamics (Governments' Financing Needs) that have received substantial attention in the literature (see Kilponen et al., 2015, for an insightful discussion) in explaining bond yield dynamics in the euro area. Second, we test the robustness of our main results by considering the use of other model selection criteria and discuss the implications of summarising the information content of individual factors using principal components by macroeconomic groups.

5.1 Macroeconomic factors vs CDS premia and debt dynamics

A substantial part of the literature on the financial crisis in the euro area has focused on the CDS premia and debt dynamics in euro area bond markets. We discussed above that selected macroeconomic factors are capable of outperforming other prominent financial indicators based on forward rates and yield spreads, like the CP-factor, in forecasting bond premia. Table 5 reports a comparison of the $\bar{R}^2$ of the macro factors models selected above with regressions based on Governments' Financing Needs (Column 3) and CDS premia during the crisis period (column 4). Results suggests that macro factor models provide significant gains over both CDS premia and debt dynamics in forecasting bond premia in two-year bonds. Moreover, evidence suggests that the superior performance of macro models holds both for core and SMP countries, although reflecting the importance of those two financial indicators in SMP countries during the crisis the explanatory gains provided by macroeconomic factors are relatively more limited in SMP than in core countries ' bond markets.

The superior performance of our macroeconomic models over financial factors is not related to the combination of several factors for many bond markets (see Tables 3 and 4). To illustrate that, Table 5 reports the gains from our multi-factor macro models to a financial model comprising both Governments' Financing Needs and CDS premia together with the CP-factor (see Column 6). On average, macro factor models outperform financial factors both prior to and during the financial crisis (adding 36% and 33% respectively). Furthermore, gains for the pre-crisis to the crisis period are significantly higher among SMP bond markets (on average 22% to 36%) than among Core ones (29% to 30%), which also stresses the relevance of accounting for macroeconomic exposures to explain the significant rise in bond premia in SMP bond markets during the crisis.

This evidence therefore suggest that the macroeconomic factors contain information relevant for risk premia analysis beyond that already in the yield curve or closely-monitored financial indicators, like CDS premia. In addition, our results for the CDS premia may also suggest a potential mispricing of those instruments in euro area bond markets during the crisis, at least relative to the macroeconomic situation, in as argued for example by Aizenman et al (2013).

5.2 Alternative Threshold Criteria

In section 3.2 we motivated our choice of the t-test threshold criteria to determine the optimal model composition on the basis of potential weaknesses of alternative selection criteria focusing on the model RSS. This section presents some quantitative evidence of their implications for our exercise. Table 6, Panel A, reports the average $\bar{R}^2$ and the average number of factors (across bond markets) of our selected models (see Tables 3 and 4). Using the t-test criterion the number of selected factors is always equal (by construction) to the number of factors that are significant at the selected level. Panel B reports the properties of the selected models using alternative model selection criteria (AIC, AICc, BIC and Mallow's Cp), with the number of selected factors in column 4 and the number of significant factors in column 5. $\bar{R}^2$ is significantly higher using any of the alternative selection criteria considered in Panel B and approaches nearly 100%. Yet, the number of significant factors using any of the other threshold methods is always below the number of factors which have been included in our preferred model, and this holds across sample periods and bond market groups (columns 6-11). Table 6 evidence confirms empirically that RSS-based threshold criteria tend to select models that display signals of overfitting.

Admittedly, however, our choice of the standard 95-percent level of significance is to some extent arbitrary. Our qualitative results are, however, not dependent on that specific choice. Panel C shows the $\bar{R}^2$ using the benchmark t-test threshold criteria with a level of 90-percent significance and a level of 99-percent significance.[32] In the case of 90-percent significance $\bar{R}^2$ is higher by approximately 8 percent than the benchmark, and in the case of the 99-percent of significance $\bar{R}^2$ is lower by approximately 7 percent.

[32] Here again there is no need to report the number of significant factors.

5.3 Are single factors by macro group enough?

Section 4.1 investigated the individual explanatory power of each macro factor. Standard factor approaches popularised by the forecasting literature in a data rich setting (e.g. Stock and Watson, 2002) rely on the fact that a single statistical factor might very well capture the information content of a full macro group. However, factors within a macro group as diverse and relevant as economic activity for example, may be far from perfectly correlated, and yet show high explanatory power with respect to bond premia, so a single factor would omit useful information.

In order to shed further light into the level of explanatory power of factors and the degree of correlation to other macro factors from their respective macro group, we report the average correlation ($avecor_{kbest,top25}$)[33] the best performer has with all the top-25 performers in each group. Figure 3 depicts the average correlation level on the x-axis, the mean $\bar{R}^2$ of k_{best} on the y-axis of each macro group. The dispersion size (in terms of $\bar{R}^2$) for each countries is indicated by the size of a circle.

Before the crisis, the average correlation among factors is fairly low at 0.3 for macro groups which exhibit the highest $\bar{R}^2$ (activity/sentiments and prices, see Section 4.1), while it is relatively higher (around 0.7) among the other macro groups. Significantly, important is that such a pattern became even more pronounced during the crisis. For example, for a crucial macro group such as economic activity, the R^2 practically doubles compared to pre-crisis levels across markets, but average correlation within the top performers in the group remained low (around 0.4). Moreover, such a pattern was widespread across euro area bond markets, as suggested by the relatively low dispersion of economic activity in Figure 3. This evidence suggests that, within important macro groups like economic activity, there were several factors with high explanatory power for bond premia that may however convey different information. In the light of this situation, extracting a single principal component to describe the whole macro group

[33] That is we compute average correlations as $avecor_{kbest,top25} = 1/K_{top25} \sum_{k_{top25}=1}^{K_{top}} corr(k_{best}, k_{top25})$

may help reduce dimensionality (e.g. Beber et al,2013), but may be inefficient to explain bond risk premia and bias the results against the role of macro factors.

Indeed, using LARS-EN and a t-test criterion for optimal factor selection, Section 4.2 shows that the optimal model for certain bond markets comprise several factors from the same macro group, especially during the financial crisis period. A single-factor selection based on statistical techniques would, therefore, lead to a mispecified factor model. We interpret those findings as illustration that selecting individual macro-finance series rather than principal components for different categories both increases transparency, and may also contribute unveiling the strong explanatory power of the individual macro factors.

6 Concluding remarks

This paper investigates the predictive power of macroeconomic factors for bond premia in the euro area markets. We show that macroeconomic factors have an important role in forecasting bond premia in euro area markets. Specifically, macro factors were statistically and economically significant prior to the crisis, but especially during the crisis period, with economic activity economic sentiment and labour market factors becoming even more relevant in most EA countries.

Our analysis, therefore, contributes to expand the available evidence on the role of macroeconomic variables in explaining bond risk premia, and in particular, during the financial crisis period. The empirical approach proposed in this paper, the Elastic Net (EN) estimation, is particularly suitable to cope with some specific challenges of such an investigation in euro area bond markets. First, it ranks the individual factors by their predictive power for bond premia without ex-ante summarising the information set of macroeconomic indicators. Second, it allows to construct parsimonious models that are, nonetheless, robust to omitted variables. Such macro models outperform standard and widely used models based on financial indicators, like the CP-factor and/or CDS premia, and can handle well the rising segmentation in EA bond markets and the significant decoupling between core and SMP countries during the financial crisis.

By shedding new light on the role of macro factors in bond markets and the feasibility of implementing an efficient variable selection in a data rich environment even in times of significant market turbulence, our results should be of interest for researchers, policymakers and market practitioners alike. First, our results provide support for the recent literature that aims at modelling the term structure of interest rates and the macroeconomy jointly to better understand the financial and debt crisis in the EA bond markets (i.e. Dewachter et al., 2014). Despite the crucial role of macroeconomic factors, the degree of heterogeneity in EA bond markets we found in this paper, however, warns against a limited number of macroeconomic variables as state variables in those term-structure models. In this sense, our results call for modelling approaches that use composite factors as state variables (see e.g. Moench, 2008).

Policy analysis could also benefit from a better interpretation of risk premia dynamics in the EA. For example, Kilponen et al. (2015) recently showed that the wide range of policy measures announced during the recent financial crisis in the euro area had a positive impact in calming the most stressed bond markets. Using high-frequency data more suitable to analyse the impact of such policy announcements, they report that macroeconomic news appeared to be less relevant to explain daily changes in bond yields. It is, however, very important to understand which part of evolution of bond yields is related to the countries' economic fundamentals, for beyond immediate market reactions, the sustainability of sovereign debt, and the efficient pricing of risks, is strongly related to the macroeconomic environment, as our findings suggest. Looking ahead, taking into account news but also trends in the euro area macroeconomy is likely to be crucial for the evaluation of the Asset Purchase Programmes introduced in early 2015 by the ECB. European policymakers as well as market practitioners could exploit the flexible modelling techniques introduced in this paper to measure such risks.

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Table 1: Summary Statistics for level bond premia at 2-year maturity

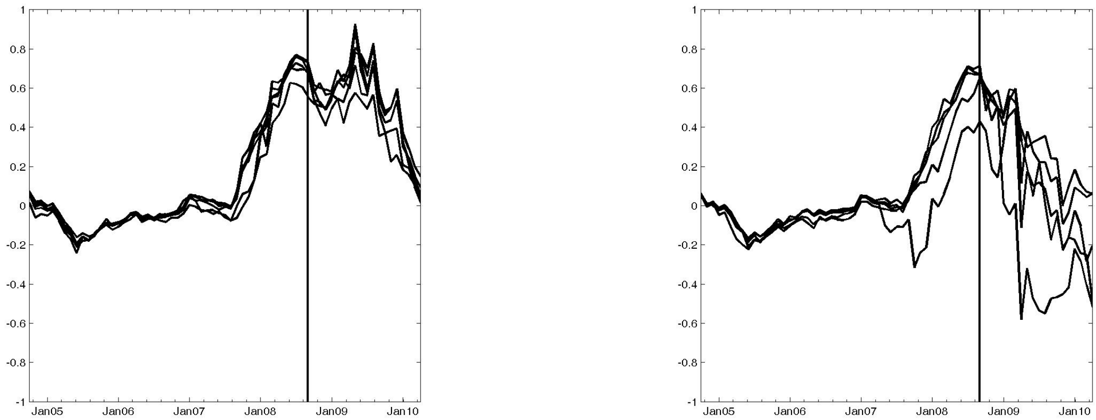
		Centered Moments				Autocorrelation		
		Mean	StDev	Skew	Kurtosis	Lag 1	Lag 2	Lag 3
Pre-Crisis	Austria	0.13	0.27	1.13	2.83	0.97	0.96	0.94
	Belgium	0.14	0.28	1.20	2.94	0.99	0.98	0.96
	Germany	0.15	0.29	1.07	2.60	0.99	0.97	0.95
	Finland	0.07	0.23	1.46	3.57	0.98	0.96	0.93
	France	0.14	0.27	1.13	2.75	0.99	0.97	0.95
	Netherlands	0.11	0.29	1.37	3.22	0.98	0.96	0.92
	Spain	0.13	0.26	1.22	2.91	0.99	0.97	0.94
	Greece	0.06	0.21	1.38	3.68	0.98	0.97	0.95
	Ireland	-0.02	0.16	1.21	4.42	0.89	0.76	0.54
	Italy	0.13	0.24	1.27	3.19	0.99	0.98	0.96
	Portugal	0.12	0.24	1.28	3.17	0.99	0.98	0.96
Crisis	Austria	0.55	0.18	-0.72	2.86	0.82	0.65	0.50
	Belgium	0.47	0.22	-0.60	1.87	0.90	0.86	0.79
	Germany	0.52	0.20	-0.49	2.65	0.81	0.59	0.38
	Finland	0.42	0.17	-1.12	3.11	0.87	0.80	0.79
	France	0.51	0.21	-0.66	3.23	0.81	0.63	0.56
	Netherlands	0.55	0.22	-0.82	3.18	0.81	0.66	0.63
	Spain	0.27	0.24	0.35	1.77	0.86	0.75	0.67
	Greece	-0.18	0.41	0.95	2.45	0.87	0.84	0.77
	Ireland	0.09	0.30	-0.07	1.98	0.81	0.70	0.64
	Italy	0.33	0.21	0.01	1.78	0.90	0.84	0.82
	Portugal	0.15	0.31	0.30	1.65	0.83	0.80	0.80

Notes: Pre-Crisis: 2005:10 - 2008:08. Crisis: 2008:09 - 2010:04.

Figure 1: 2-year bond premia in the Euro Area bond markets

(a) Core countries

(b) SMP countries



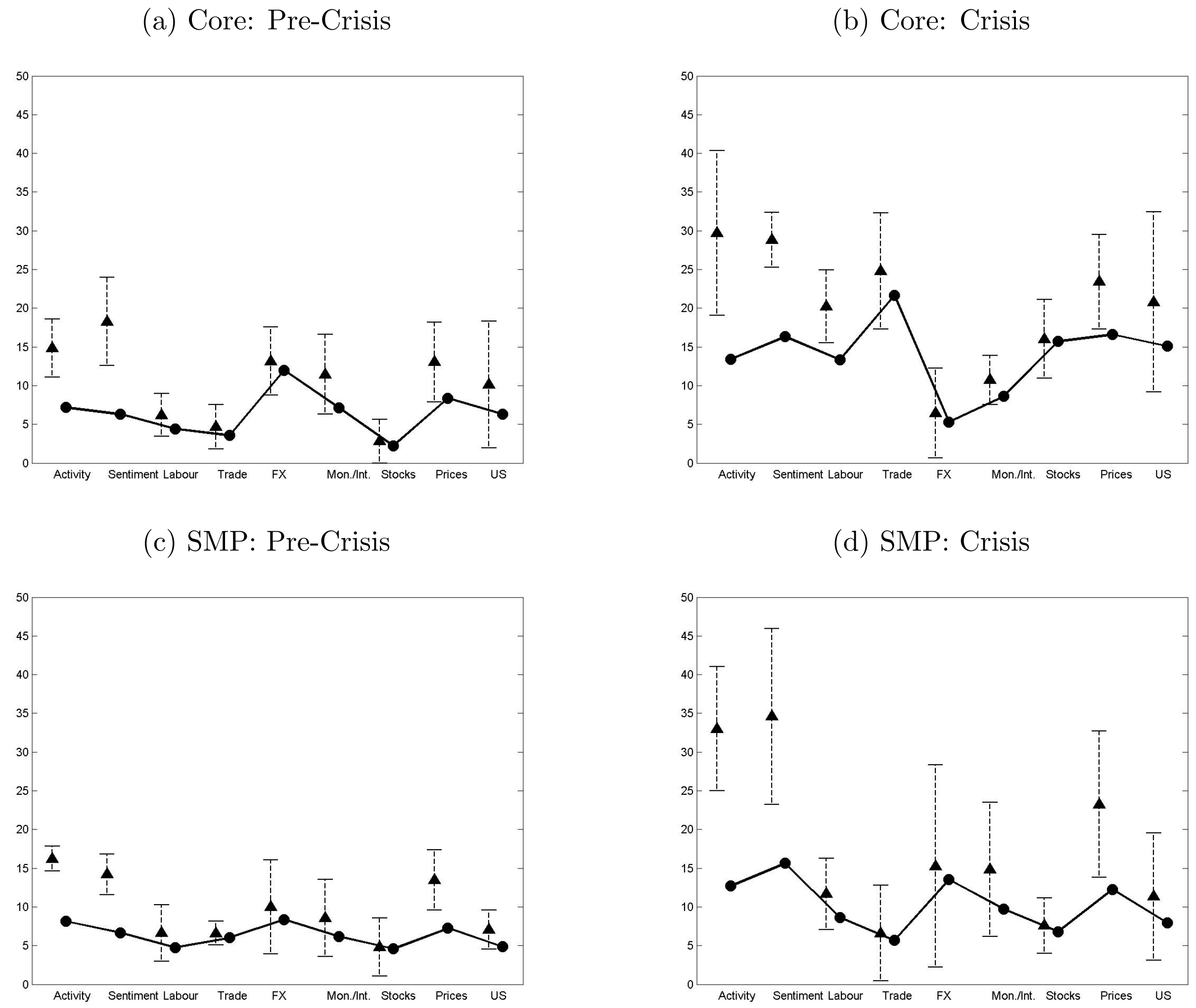
Notes: Panels (a) and (b) depict 2-year bond premia in Core (Austria, Belgium, Germany, Finland, France and the Netherlands) and SMP (Spain, Greece, Ireland, Italy and Portugal) bond markets respectively. The vertical line in September 2008 divides our sample in Pre-Crisis (2005:10 - 2008:08) and Crisis (2008:09 - 2010:04) periods.

Table 2: Correlation coefficients for bond premia and yields at 2-year maturity

	Level			Stationarised		
	All	Core	SMP	All	Core	SMP
Excess returns						
Pre-Crisis	0.65	0.76	0.57	0.95	0.99	0.91
Crisis	0.30	0.78	0.48	0.68	0.92	0.82
Yields						
Pre-Crisis	0.93	0.94	0.93	0.99	0.99	0.99
Crisis	0.31	0.64	0.49	0.73	0.98	0.59

Notes: The upper and lower panel report the average correlations for 2-year bond premia and yields respectively across country groups. The left columns contain the average correlations for raw excess returns (as shown in Figure 1) and yields, while the right columns show average correlations for stationarised bond excess returns and yields. Pre-Crisis sample is 2005:10 - 2008:08 and the Crisis one 2008:09 - 2010:04.

Figure 2: Macro factors' marginal explanatory power: Average distribution across countries and periods



Notes: Figures (a) to (d) report R^2, that is of predictive regressions using a single macro factor ($rx_{t+12}^{(n)} = \beta_0 + z_t\beta + \epsilon_{t+12}$). Figures (a) and (b) refer to Core (Austria, Belgium, Germany, Finland, France and the Netherlands) and Figures (c) and (d) to SMP (Spain, Greece, Ireland, Italy and Portugal) bond markets. In each figure, triangles represent the highest R^2 of each macro group averaged across countries. Averaged across countries, the solid line represents the mean value of the top performers quartile of each macro group, the left and the right panel refer to the Pre-Crisis (2005:10 - 2008:08) and Crisis (2008:09 - 2010:04) periods, respectively. Whiskers at each triangle denote the dispersion of highest R^2 across countries.

Table 3: Model Composition of LARS-EN ($rx^{(2)}$)

Bond market	Sample Period	$\bar{R}^2$	Name	Sign	$\bar{R}^2$ of only CP-fac.	Macro Group (Factor number)
Austria	Pre-Crisis	50	Unemployment	+	7	US (124)
			Inflation perceptions (EC consumer surveys)	+		Sentiment (50)
			OIS spread (1-year)	-		Mon./Int. (95)
	Crisis	77	CP-Factor	+	45	
			Expected business conditions (EC business surveys)	+		Sentiment (60)
			Industrial Production (Manufacturing,EC business surveys)	-		Activity (Country, 13)
			Exports to EA	-		Trade (Country, 77)
Belgium	Pre-Crisis	40	Savings expectations (EC consumer surveys)	-	12	Sentiment (48)
			Inflation perceptions (EC consumer surveys)	+		Sentiment (50)
			OIS spread (1-year)	-		Mon./Int. (95)
			Services Price inflation	+		Prices (111)
	Crisis	59	Inflation expectations (EC consumer surveys)	-	30	Sentiment (51)
			CP-Factor	+		
			Employment	-		Labour (73)
Germany	Pre-Crisis	23	Inflation perceptions (EC consumer surveys)	+	4	Sentiment (50)
			Saving expectations (EC consumer surveys)	-		Sentiment (48)
	Crisis	76	CP-Factor	+	31	
			Expected business conditions (EC business surveys)	+		Sentiment (60)
			Imports from EA	-		Trade (Country, 76)
			Employment	-		Labour (73)
			Building Permits (residential)	+		Activity (Country, 33)
Finland	Pre-Crisis	63	CP-Factor	+	25	
			Retail sales	-		Activity (26)
			Passenger Car registrations	-		Activity (19)
			Saving expectations (EC consumer surveys)	-		Sentiment (48)
			Inventories (EC business surveys)	-		Sentiment (38)
			Business outlook	-		US (127)
			Stock market index	-		Stocks (Country, 70)
	Crisis	60	Industrial Production (EC business surveys)	-	18	Activity (Country, 16)
			Retail Trade	+		US (126)
France	Pre-Crisis	34	Inflation perceptions (EC consumer surveys)	+	5	Sentiment (50)
			OIS spread (1-year)	-		Interest rates (95)
			Business outlook	-		US (127)
	Crisis	47	CP-Factor	+	47	
Netherlands	Pre-Crisis	35	Passenger Car registrations	-	17	Activity (19)
			CP-Factor	+		
	Crisis	54	Expected business conditions (EC business surveys)	+	13	Sentiment (60)
			Exports to EA	-		Trade (Country, 65)
			Unemployment outlook (EC consumer surveys)	-		Sentiment (Country, 39)

Notes: The first column indicates the bond market. The second column indicates the sample period. The third column reports $\bar{R}^2$ for equation (1) using the EN criterion (2) for each Core bond market. The fourth column describes the factor. Column 5 reports the estimated sign of each factor. Column 6 shows the $\bar{R}^2$ of the single CP-factor model. Column 7 indicates the macro group and in brackets the series number. (Country) refers to a country-specific series. Pre-Crisis: 2004:10 - 2008:08. Crisis: 2008:09 - 2010:04.

Table 4: Macrofactor models in predictive regressions for bond risk premia: performance and composition (*cont*)

Bond market	Sample Period	$\bar{R}^2$	Name	Sign	$\bar{R}^2$ of only CP-fac.	Macro Group (Factor number)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Spain	Pre-Crisis	22	CP-Factor	+	22	
	Crisis	67	Production perceptions (EC business surveys)	-	10	Sentiment (Country, 39)
			Retail sales	+		Activity (Country, 29)
			Building Permits (residential)	-		Activity (33)
			Unemployment rate	+		Labour (69)
Greece	Pre-Crisis	53	CP-Factor	+	12	
			Industrial Production (EC business surveys)	-		Activity (4)
			Passenger Car registrations	-		Activity (19)
			Demand perceptions (EC business surveys)	-		Sentiment (Country, 62)
			Industrial Production (EC business surveys)	+		Activity (17)
			Inventories (EC business surveys)	-		Sentiment (38)
			Retail sales	+		Activity (Country, 29)
	Crisis	40	Inflation perceptions (EC consumer surveys)	+	0	Sentiment (Country, 48)
Ireland	Pre-Crisis	25	Financial expectations (EC consumer surveys)	-	-2	Sentiment (45)
			Passenger Car registrations	-		Activity (19)
	Crisis	19	Business Climate (EC business surveys)	-	2	Sentiment (63)
Italy	Pre-Crisis	46	CP-Factor	+	28	
			OIS spread (1-year)	-		Mon./Int. (95)
			JPY/EUR Exchange rate	+		FX (84)
			Inflation perceptions (EC consumer surveys)	+		Sentiment (50)
			Saving expectations (EC consumer surveys)	-		Sentiment (48)
	Crisis	50	Retail sales	-	2	Activity (Country, 29)
			Industrial Production (EC business survey)	+		Activity (Country, 17)
			Economic conditions (EC business surveys)	-		Sentiment (49)
Portugal	Pre-Crisis	29	CP-Factor	+	15	
			Industrial goods inflation	+		Prices (121)
			Saving expectations (EC consumer surveys)	-		Sentiment (48)
	Crisis	43	Inventories (EC business surveys)	-	16	Sentiment (59)
Summary						
All	Pre-Crisis	38			13	
	Crisis	54			19	
Core	Pre-Crisis	41			12	
	Crisis	62			31	
SMP	Pre-Crisis	35			15	
	Crisis	44			6	

Notes: See table 3

Table 5: Macro factor model performance relative to standard financial indicators

Country	Sample	Financing Needs	CDS spreads	CP-Factor	All
(1)	(2)	(3)	(4)	(5)	(6)
All	Pre-Crisis	37		25	26
	Crisis	45	52	34	33
Core	Pre-Crisis	39		29	29
	Crisis	50	61	32	30
SMP	Pre-Crisis	34		20	22
	Crisis	38	40	38	36

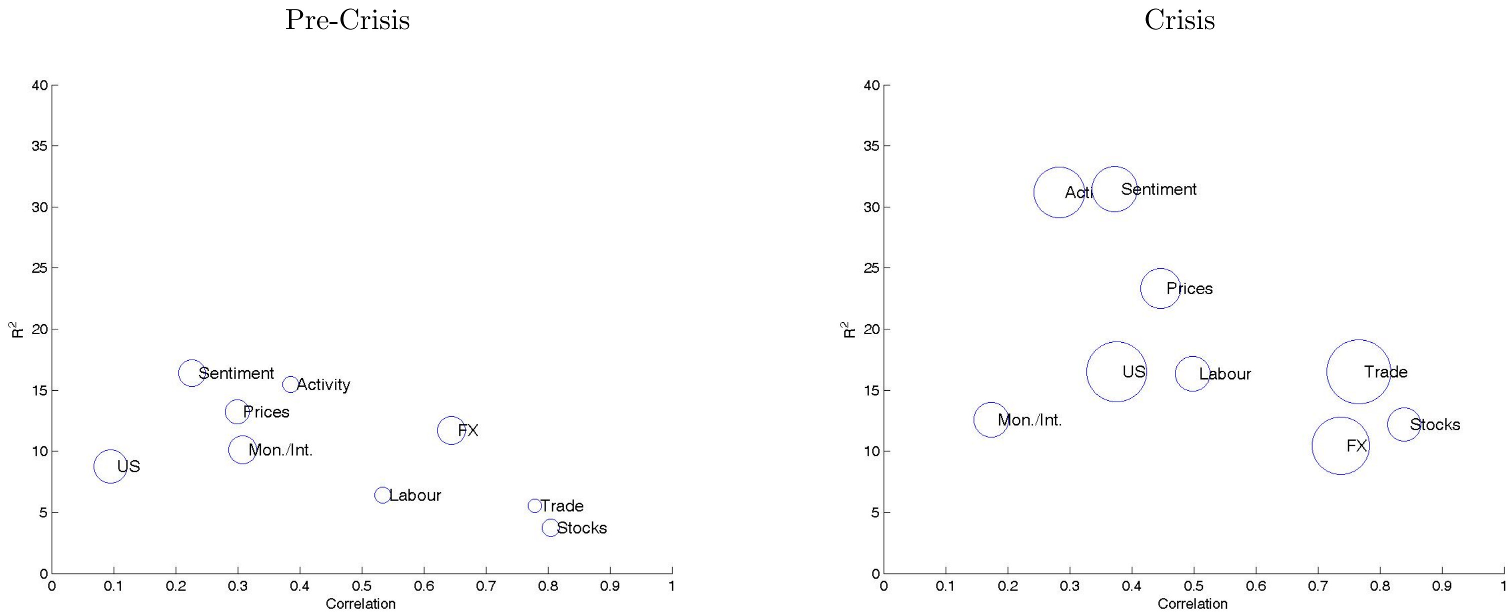
Notes: The table reports the average improvement of the macro factor-based models over simple linear regressions using selected financial indicators on average across All, Core (Austria, Belgium, Germany, Finland, France and the Netherlands) and SMP (Spain, Greece, Ireland, Italy and Portugal) bond markets. From left to right, Column (1) lists the corresponding bond market group, (2) the sample period, Columns (3), (4), (5) and (6) report the average improvement using governments financing needs, CP-factor, Credit Default Swap spreads, respectively, and all three of them. Pre-Crisis period: 2004:10 - 2008:08. Crisis period: 2008:09 - 2010:04.

Table 6: Alternative Threshold criteria ($rx^{(2)}$)

		All countries			Core countries			SMP countries		
		$\bar{R}^2$ (%)	#Fac	#Fac (95% sig.)	$\bar{R}^2$ (%)	#Fac	#Fac (95% sig.)	$\bar{R}^2$ (%)	#Fac	#Fac (95% sig.)
Panel A $T-$test criterion										
95% CI	Pre-Crisis	38%	4		41%	4		35%	4	
	Crisis	54%	3		62%	3		44%	2	
Panel B Alternative Model Selection Criteria										
AICc	Pre-Crisis	86%	20	17	89%	21	18	82%	18	15
	Crisis	88%	8	7	88%	9	8	87%	8	6
AIC	Pre-Crisis	96%	30	25	98%	31	27	94%	29	23
	Crisis	98%	14	13	98%	14	13	98%	14	13
BIC	Pre-Crisis	96%	30	25	98%	31	27	94%	28	23
	Crisis	98%	14	13	98%	14	13	98%	14	13
Mallow's Cp	Pre-Crisis	70%	13	11	82%	16	14	56%	9	6
	Crisis	92%	12	11	94%	13	12	90%	11	10
Panel C Alternative $T-$test criteria										
90% CI	Pre-Crisis	46%	5		53%	6		38%	4	
	Crisis	61%	3		69%	4		52%	3	
99% CI	Pre-Crisis	31%	2		35%	2		27%	2	
	Crisis	48%	2		55%	2		39%	1	

Notes: Panel A summarizes the results of the benchmark model selection method (t-stat hard-thresholding) as well as benchmark level of significance (95%). Panel B reports the results of four alternative model selection criteria, AICc, AIC, BIC and Mallows Cp .Panel C reports the results of the benchmark selection method (t-stats hard-thresholding) at different levels of significance. The first column indicates the threshold criteria/method which is used to select the model. The second column indicates the sample period. Column 3 and 4 reports the average $\bar{R}^2$ and the average number of factors of the selected models across the euro area, respectively. Column 5 reports the number of selected factors for the other four model selection criteria which are significant at the 95% level. Columns 6 to 11 similarly report the averages for the Core (Austria, Belgium, Germany, Finland, France and the Netherlands) and SMP (Spain, Greece, Ireland, Italy and Portugal) groups. Pre-Crisis: 2004:10 - 2008:08. Crisis: 2008:09 - 2010:04.

Figure 3: Macro factors predictive power and cross-correlation: Average distribution across countries in pre-crisis and crisis



Notes: The x-axis indicates the average correlation (across countries) the maximum-scoring factor of each macro group has with the top performers quartile of the same macro group. The y-axis indicates the highest R^2 reached within each macro group. The size of the circle reflects the cross-country dispersion of the R^2. The left and the right panels refer to the Pre-Crisis (2005:10 - 2008:08) and Crisis (2008:09 - 2010:04) periods, respectively.

Acknowledgements
The authors would like to thank Ricardo Gimeno, Matteo Ciccarelli, Frank Smets, Jean-Charles Wijnandts and conference participants at the 28th Meeting of the European Economic Association, Gothenburg, the Econometric Society Australasian Meeting, Sydney, and the 2015 RCEA Money and Finance Workshop "The Great Recession: Moving Ahead", Rimini, and the October 2015 3L Finance Workshop, Brussels for helpful discussions and comments.

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ISSN 1725-2806 (online)
ISBN 978-92-899-2186-2
DOI 10.2866/633700
EU catalogue No QB-AR-16-055-EN-N